Instituto de Economía
Facultad de Ciencias Económicas y de Administración
Universidad de la República - Uruguay

The efficiency of Uruguayan secondary schools: Evidence based on PISA 2015 data

Paola Azar- Federico González- Leonel Muinelo Gallo

INSTITUTO DE ECONOMÍA
Serie Documentos de Trabajo
Dic., 2018
DT 14/2018

ISSN: 1510-9305 (en papel)
ISSN: 1688-5090 (en línea)

Forma de citación sugerida para este documento: Azar, P., González, F., Muinelo-Gallo, L. (2018) "The efficiency of Uruguayan secondary schools: Evidence based on PISA 2015 data". Serie Documentos de Trabajo, DT 14/1998. Instituto de Economía, Facultad de Ciencias Económicas y Administración, Universidad de la República, Uruguay.

Eficiencia en los liceos en Uruguay. Evidencia basada en datos de PISA 2015

Paola Azar (*)
Federico González (*)
Leonel Muinelo-Gallo (*)

Resumen

Aunque el gasto en educación en Uruguay aún es limitado, su mejor uso también podría marcar una diferencia en cuanto a los resultados educativos obtenidos. Este trabajo analiza la eficiencia educativa de un conjunto de escuelas públicas y privadas uruguayas, y explora sus principales determinantes utilizando datos de PISA para 2015. La eficiencia se estima utilizando los puntajes PISA, ajustados por la condición socioeconómica de los estudiantes, como variable de resultado en un Análisis de Envolvente Datos y explicado por un conjunto de variables contextuales aplicando regresiones truncadas con *bootstraps*. Los resultados muestran altos niveles de ineficiencia en los liceos de Uruguay, con una considerable dispersión en la distribución del indicador. El aumento de la eficiencia se asocia con el tamaño del centro, su ubicación geográfica, la gestión privada del mismo y la presencia de personal no docente.

Palabras clave: PISA, efficiency, DEA, private ownership

Código JEL: C14, H52, I21

(*) Instituto de Economía, Facultad de Ciencias Económicas y de Administración, Universidad de la República. pazar@iecon.ccee.edu.uy; fgonetch@gmail.com; lmuinelo@iecon.ccee.edu.uy

The efficiency of Uruguayan public secondary schools. Evidence based on PISA 2015 data

Paola Azar
Federico González
Leonel Muinelo-Gallo

Abstract

While Uruguayan public education spending is limited so that increasing funding could still improve schooling outcomes, a better use of the current resources could also make a difference. This paper analyses the efficiency performance of a set of public and private schools and explores its main drivers based on PISA-2015 data. Efficiency is estimated by using PISA marks adjusted by the student socioeconomic condition as outputs in a Data Envelopment Analysis (DEA) and it is regressed on a set of explanatory variables by applying bootstrapped truncated regressions. Results show high inefficiencies for the average Uruguayan school with a considerable dispersion in the efficiency attainments. Efficiency gains are associated to school size, location, private management and the presence of non-teaching staff.

Keywords: PISA, efficiency, DEA, private ownership

JEL Classification: C14, H52, I21

1. Introduction

Over the last years, the need to expand human capital in the context of growing enrolment rates and tight budget constraints has turned efficiency in education into a powerful argument. The underlying rationale is that if available resources are not used to their potential, just adding more would not necessarily improve the schooling results. The concept became particularly appealing for developed countries showing a persisting inconsistency between the range of education investments and the improvement of their learning outcomes (Hanushek 2003). But gradually, the efficiency approach has also gained influence in developing countries, which comparatively face harder restrictions to increase fiscal resources and often lag behind in the international test achievements (Hanushek and Woessmann 2012, IMF 2014).

This paper brings the efficiency debate into the context of a long lasting concern about the poor education outcomes in Uruguay. Though regarded as an upper-middle income economy, with a high Human Development Index, the student performance is problematic in the country, particularly in secondary schooling. In 2010 the proportion of 15-24 year-olds who have completed secondary school has been 29.7%, one of the lowest in Latin America and 2.5 times below the OECD average (INEEd 2014). Moreover, one third of 15-year-old students had repeated a grade, which is the fourth highest record among the countries participating in the Programme for International Student Assessment (PISA) (OECD 2017).

The Uruguayan cumulative spending per student aged 6 to 15 is USD 20,000 PPP, a figure that poses the country among those where a higher expenditure is expected to positively affect schooling performance (Santiago et al. 2016). Indeed, per student spending is one third of the OECD's average and lower than in Chile, for example. However, the figures also show that if the country had the same per capita GDP as the OECD average, it would achieve better PISA scores but not so much as to reach out the OECD standards (OECD 2017). Therefore, relevant as it is, the resource endowment restriction does not seem to be an exclusive shortcoming.

This paper assesses whether a better resource use can lead to improvements in the learning performance at the high-school level in Uruguay and explores which driving forces are more likely to enhance it. The empirical approach considers a three-step methodology based on Uruguay PISA 2015 dataset. We first estimate fixed effect regressions of the PISA scores on a set of student background features to obtain an adjusted PISA score (Naper 2010). Next, the new score is taken as an output in a Data Envelopment Analysis (DEA) in order to obtain efficiency scores at the high-school level (Farrell 1957). Then, in a third stage, we estimate bootstrapped truncated regressions models to account for possible contextual influences over the school efficiency path (Simar and Wilson 2007).

A vast literature has used planning and resource allocation techniques to discuss education policies and its results.[1] Among the studies applying a DEA, some have focused on cross-country comparisons (Afonso and St. Aubyn 2006, Afonso et al. 2010,Schwellnus2009) while others have considered the school as the unit of analysis. This literature has worked on both, PISA datasets (Agasisti 2013, Mancebon et al. 2012,Agasisti and Zoido 2015) and country-specific records (Thieme et al. 2013 for Chile, Mancebón and Muñiz 2008 for Spain, Portela et al. 2012 for Portugal,Nghiem et al. 2016 for Australia). Each of them introduces the family influence of students on their leaning records in a different way: some take the socioeconomic variables as one input in the efficiency computation; others try to correct for this effect by applying multi-level frontier approaches (Thieme et al. 2013, Mancebon and Muñiz 2008). Naper (2010) estimates school fixed effect regressions of individual education results on a set of personal traits. This is the method we follow in the present study.

A group of analyses also explores how efficiency is shaped by the impact of some contextual variables by employing a parametric approach (with truncated, Tobit and even OLS regressions). They find that the quality of educational resources, the student or teacher attitudes, school competition in the neighborhood or the mechanisms for hiring teachers are important efficiency drivers (Agasistiand Zoido 2015, Agasisti 2013, Naper 2010). Additionally, some scholars have discussed the efficiency gains from private or public school ownership (Calero and Escaríbul 2007, Perelman and Santin 2011, Mancebon et al. 2012, Crespo et al. 2014). However, results about the superior efficiency results of either form of organization are not conclusive.

In Uruguay, the studies based on PISA data conclude that individual and school socioeconomic contexts are the main drivers of the education performance (Llambí and Perera 2009, Doneschi 2017, ANEP 2017). Efficiency at the school level has been tackled just by Santin and Sicilia (2015) for public institutions. Based on PISA records for 2009 and 2012 the authors find that education outputs could be improved approximately 20% to attain efficiency. Also, that efficiency gains depend on a low number of repeaters, scarce apprehension against mathematics and more teacher qualification. The present work goes back to the efficiency discussion taking the most recent PISA results and including both private and public schools.

The focus of this paper's discussion is rather different from previous studies. First, we study the high-school performance to learn about which issues other than the socioeconomic environment affect the school educational results. Second, by establishing a fear comparison in terms of inputs across the school sample, we provide evidence to discuss whether the private or public ownership bears any effect in producing better educational outputs. Third, our technical efficiency assessment does not preclude recognizing that secondary schools in the country are in considerable need of greater funding.

[1] See Johnes (2015) for a survey.

The paper is structured as follows. The key features of the educational system under analysis are presented in Section 2. Next, we describe the methodology and in Section 4 the data and empirical approach. We discuss results in Section 5 and section 6 concludes.

2. Background

The Uruguayan schooling system is organized in four stages: early childhood and pre-primary education (below 3 to 5 years old), primary education (from 6 to 11), lower secondary education (ages 12 to 14) and upper secondary education (ages 15 to 17). The tracks in secondary education contain different alternatives: general, technical or basic professional training (in this last case, for those aged at least 15). School attendance is compulsory from the age of 4 to the end of upper secondary education. Public education prevails: 87% of secondary students are enrolled at public institutions. Over that total, about 75% of secondary students attend general programs (INEEd 2017). Private high-schools are 27% of the total, charge tuition fees and do not receive any direct government funding, though they are exempted or alleviated from some tax charges. Over half of them are located in Montevideo, the capital city (INEEd 2014).

Conducted by the Organization for Economic Co-operation and Development (OECD), PISA evaluates 15 year-old students across 72 countries, no matter the institution and grade at which they are actually enrolled. The assessment measures the ability of students to understand and employ written and mathematical tools to interpret and solve situations under a variety of contexts (OECD 2016a). PISA also provides background information on each individual (personal and family characteristics) and her school, based on questionnaires answered by parents and school principals. Uruguay participates in PISA since 2003 and the assessment for 2015 is the latest available. In that year the survey covered 6.000 students from public and private, technical and rural secondary schools, distributed across a total of 236 educational centers (over a total of 44.097 students over 943 centers).[2]

Globally, PISA 2015 implemented a set of changes to the assessment mode (from paper-based to computer-based); to the procedure to scale results and make them comparable and to the test design. Different from previous waves, in PISA 2015 "lack of response" is no longer computed as a "wrong response". The change impacted the scoring of Uruguay, for the country is one of the three with the highest proportion of test-takers who had traditionally left questionnaires and tasks unanswered (25% of the total -ANEP 2017). However, even after considering that improvement, Uruguayan performance still reflects a set of weaknesses which come to light in the international comparison. Of all the countries participating in PISA, Uruguay is among the 4 with the highest

[2] Schools are randomly chosen considering its size and the same technique applies to students within each school.

prevalence of repetition. Approximately 90% of students enrolled in secondary education have repeated at least once over their educational history. On top of this, Uruguay has the fifth position when countries are ranked according to the strength of the link between socioeconomic conditions and schooling performance (OECD 2016a). Thus, instead of counterbalancing the socioeconomic inequalities among students the education system seems to be reproducing them.

Regarding PISA scoring, the country performance has been above the regional average but poor in relation to the OECD (Table 1).

Table 1. Comparative PISA records across countries and time

	Mathematics			Reading		
	2009	2012	2015	2009	2012	2015
Uruguay	427	409	418	426	411	437
OCDE average	496	494	490	501	496	493
Argentine	388	388	----	398	396	----
Brazil	386	391	377	412	410	407
Chile	421	423	423	449	441	459
Colombia	381	376	390	413	403	425
Mexico	419	413	408	425	424	423
Canada	527	518	516	524	523	527
Korea	546	554	524	539	536	517
Finland	541	519	511	536	524	526
Hong Kong-China	555	561	548	533	545	527

Source: ANEP (2017)

PISA ranges the difficulty of tasks from the highest (Level 6) to Level 1b at the bottom of the scale. Level 2 is recognized as a standard minimum competence threshold. In Uruguay, Levels 1 and 2 gather the highest share of students. For Reading, 23.2% of students belong to Level 2 and 39% are below it (the share is 20.1% in the OECD). Top performers in reading are 2.5% in Uruguay and 8.3% in the OECD. In the case of Mathematics, 52% of students do not reach the baseline Level 2 while the figure is 23.4% in the OECD. Top performer students are 1.7% *vis-à-vis* 10% in the average of OECD countries (OECD 2016a). Additionally, PISA has consistently shown that students attending private institutions outperform those of public and technical ones. However, the results for private schools in PISA 2015 seem to be driven by their having pupils with more favorable background. Thus, after accounting for differences in socioeconomic circumstances, public and private PISA scoring do not differ significantly (Doneschi 2017, ANEP 2017).

Following from the outstanding effect of socioeconomic conditions, research into how schools operate has remained rather hidden. However, the educational results in the country might also be associated to deficiencies in the school input endowment and in failures on how the directive school boards and the public education authorities manage them. According to PISA surveys to the school principals, the schools face serious obstacles. The average student attends high-schools where 57% of teachers are certified, while the percentage across OECD countries is 87%. The prevalence of teacher absenteeism is the highest in the region: 6 out of 10 students are affected by this problem, while the proportion is less than 2 for the OECD and 3.5 for Chile (the second highest figure in the region). Besides, 30% of students attend a school where principals perceive that teachers are not well prepared to teach classes. The incidence of this problem reduces to 12% in the OECD (ANEP 2017).

The share of Uruguayan students affected by the shortage or low qualification of the school non-teaching personnel is 55% and 40%, respectively. Together with the ones for Costa Rica, these are the highest regional records, far from the OECD averages: 35.4% and 19%, respectively. By contrast, the proportion of students receiving the impact of low availability or quality of material resources and infrastructure is rather low or aligned with the regional standards.

According to data, these problems mainly take place in public institutions. Indeed, beyond their education expenditures they seem to be connected to how schools operate. Consider that hiring practices imply that the least experienced and less-stable teaching staff is assigned to the most disadvantaged contexts (Filgueira and Lamas 2005). Moreover, the number of available posts for school principals and other administrative or support personnel are not enough to cover all schools and the period until a vacant position is occupied is often very extensive (INEEd 2014).

In this context, the present efficiency analysis discusses the effects of improving the relative performance of schools on the education outcomes. Particularly, it explores whether Uruguayan schools differ as much as envisaged in terms of the inputs they employ and the outputs they get.

3. Methodology

We compute the educational technical efficiency at the school level according to a non-parametric technique followed by a regression analysis to explore some of its determinants. Technical efficiency can be understood as the competence with which a sample of decision-making units (DMUs) transforms inputs into outputs (Farrell 1957). The DMUs are organizational units which produce different outputs using inputs under a certain production technology implied in their production functions. Our approach flows from the long standing idea that there is a relationship between educational resources and student achievements that can be thought as a production function (Hanushek1979).

Since the well-known Coleman report on US education system (Coleman et al. 1966) a great amount of research has provided support for family socioeconomic background as the key to account for student achievement (Hanushek 2003). Therefore, parental socio-economic and cultural status is often considered as relevant inputs into the education production process.

However, as this paper aims at comparing efficiency achievements at the school level, particular care should be taken in the input and output selection. To capture the part of the student outcomes attributable to schools we need to untangle them from the effect of student characteristics so that the specification is consistent with a *school* production process. Taking this caveat into consideration, our empirical strategy has three steps: firstly, we build school level outputs by controlling for the student characteristics; next, we identify whether schools with similar resources obtain different efficiency results and finally, we explain these differences considering the role of contextual or environmental factors.

3.1. First step: getting school fixed effects

In the literature dealing with efficiency at the school level, the pupil background is often included into the efficiency computation. Some studies directly take student features as inputs under the assumption that they are essential to account for the schools' learning achievement (Agasisti 2013, Santin and Sicilia 2015). In others, these are taken as inputs but the non-parametric technique is transformed so to capture those efficiency drivers depending on pupils or on the school type (Portela and Thanassoulis 2001, Mancebón et al. 2012). In this paper, we take a different perspective: following Naper (2010) we introduce an output-transformation before the efficiency computation. Thus, the PISA score for each *i* student in the sample (Y_i) is regressed on a set of individual and family features at the student level (matrix S) and on a group of dummy variables which identify the high-school where the student attends (vector C) as in Equation (1):

$$Y_i = \beta_0 + S_i \beta_1 + \alpha C_i + \varepsilon_i \qquad (1)$$

where ε_i is an error term and α will be interpreted as the average relative effect of each particular school on the student learning achievement. This coefficient shows the part of the PISA record that can be assigned to the particular school effect and it is used as the output variable in the efficiency computation.

3.2. Second step: Data Envelopment Analysis

Data Envelopment Analysis computes efficiency based on the construction of a production possibility frontier that defines which linear combination of observed output-input bundles is feasible within a sample of DMUs. Efficiency would be given by the relative distance between each specific DMU and the frontier. Therefore, the performance of one DMU is rated in relation to the best achieved performance: it is a relative not an absolute measure (Ramanathan 2003).

Following Charnes et al. (1978), the efficiency level of non-frontier units can be estimated using a linear programming methodology that can be solved as an input minimizing scheme or as its dual, an output-maximizing problem. In the first case, the efficiency estimation would be "input-oriented" as DMUs try to minimize the input use to obtain the current level of output. Inputs are those productive resources which use is under the control of the DMUs. Alternatively, under an "output oriented" design, efficient units should produce the greatest output for a given input level.

The relative efficiency of a DMU can be estimated as the ratio of the weighted sum of its outputs to the weighted sum of its inputs. Weights indicate the relative importance of an additional unit of output or input. In a market economy, the input weights are given by the relative market price of the different inputs. If the relative value of outputs could also be assigned, the corresponding ratio would show the extent to which a DMU is purchasing its input mix efficiently (that is, at the lowest possible prices). This would describe the "allocative efficiency". Instead, when input and output weights are allowed to vary freely, the DMU's efficiency is assessed using the weights most favorable to its own circumstances without imposing restrictions. This provides a measure of "technical efficiency". In its output-oriented version, the program aims at maximizing the output production subject to a given resource level. For a particular DMU (j) the problem is:

$$max.\, \delta_j \quad (2.1)$$

subject to:

$$y_j - Y\lambda \leq 0 \quad (2.2)$$

$$x_j - X\lambda \geq 0 \quad (2.3)$$

$$n1'\lambda = 1 \quad (2.4)$$

$$\lambda \geq 0 \quad (2.5)$$

where δ_j, is the "output-efficiency score", the optimal solution to this problem; X is an input matrix with dimensions ($k * n$) being k the available inputs for each DMU and n the number of DMUs within the sample; Y is an output matrix with dimensions ($m * n$) being m the outputs of each DMU, and λ is a ($n*1$) vector of weights used to compute the location of an inefficient school if it were to become efficient.

In (2.1) δ_j is a scalar that satisfies $1/\delta_j \leq 1$ and represents the proportion by which output y_j needs to increase for DMU$_j$ to reach the production possibility frontier. The method also brings out indicators of relative efficiency within the sample of individuals under analysis. If $1/\delta_j < 1$ the DMU$_j$ is within the frontier (i.e. it is inefficient), while if $\delta_j = 1$ the DMU$_j$ is on the efficiency frontier (i.e. efficient). These DEA scores are used to build ordinal rankings measuring the relative performance of DMUs.

Equation (2.2) stands for the "output constraint". It indicates that the weighted sum of outputs from all DMUs in the sample must be greater than or equal to the potential output for DMU$_j$,given the "input constraint" in equation (2.3). Each element in vector λ represents the weights with which the DMU replicates the behaviour of the others and follows its on practices in the use of inputs to produce outputs.

In the first applications, Charnes et al (1978) solved the problem under Constant Returns to Scale (CRS). This means assuming that all DMUs are working at their technically most efficient scale and able to scale inputs and outputs linearly without increasing or decreasing efficiency. Banker et al. (1984) were pioneer in considering Variable Returns to scale (VRS). Under this assumption, DMUs are not operating at their optimal scale and the envelopment is formed by the multiple convex linear combinations of best practice DMUs: these are a closer reference for the one under analysis. The convexity condition is included in restriction $n1'\lambda = 1$ (equation 2.4).

The maximization problem is solved for every DMU in the sample. In each case the method identifies peers: these are the reference points where an inefficient DMU targets to move from the Farrell efficient point (projection on the frontier) to an optimal point (where the same output is obtained with less inputs). For inefficient units, the difference between the output target and the actual one is called slack. It shows the scope to which ideally expand one output, even after it has been increased by the range given by the efficiency score (Ramanatham, 2003).

In the present paper, the DEA takes an output-oriented specification, understanding that the great challenge of schools is improving the outcomes they get from their current resources, not reducing the input use. Besides, the analysis considers VRS so that each school is compared to others with a similar resource endowment and efficiency is computed relative to the school's own dimension.

3.3. Third step: variables affecting efficiency scores

Several environmental characteristics influence the efficiency results and lie beyond the control of the DMUs. These are considered as non-controllable inputs because they cannot be directly manipulated by the producer but do shape the DEA estimates$(\widehat{\delta_i})$. To account for this, in Equation (3) the DEA efficiency scores are regressed on a set of exogenous factors that might explain them (*Z*):

$$\hat{\delta}_i = a + Z_i\theta + \varepsilon_i \qquad (3)$$

where *i* refers to each DMU in the sample, a is a constant, θ is the vector of parameters assessing the influence of non-discretionary inputs (Z_i) on efficiency, and ε_i is a statistical noise.

DEA efficiency scores may be seen as corner solutions because they are continuous variables limited from above and below that take value 1 with a positive probability. In order to respect this bounded domain, Equation (3) is estimated by using truncated regressions (McDonald 2009, Simar and Wilson 2011).[3]

The regression analysis must consider that DEA efficiency scores present two kinds of biases: one, because they are dependent on each other so they are serially correlated in an unknown way. The other because the non-discretionary variables might be correlated to the error term through the relationship between the non-discretionary inputs and the outputs used to estimate the scores. These correlations disappear asymptotically, so the indication is to apply bootstrapped truncated regressions (Simar and Wilson 2011).

4. Data

This study uses the student individual data collected by the PISA questionnaires for Uruguay in 2015. Based on these, the efficiency analysis is performed at the school level taking also information about the school's organization, resources and decision-making processes provided to PISA by the school principals. In each step, we apply the student and school weights proposed in the PISA dataset.

The sample is comprised by a set of private and public high-schools situated in Montevideo (the country's capital city) and in the country's provinces (departments), which operate either upper-secondary or a combination of lower and upper secondary education levels (complete cycle schools). Lower-secondary schools (covering grades 1st to 3rd, that is students theoretically aged 12 to 14) have been excluded from the analysis because any 15-year old currently attending these centers has to be a repeater.[4] Also technical schools have been removed from the sample. They combine regular secondary education contents with vocational training at a range of different occupations. Hence, their educational focus and the sort of resources they use differ from the rest of secondary education institutions, which might also introduce biases to the PISA results. Finally, repeater students at complete cycle schools have been also discarded. This facilitates comparisons: in upper-secondary schools the students aged 15 *per force* are not repeaters and repeaters are a little share at private high-schools.

[3] This truncation approach underlines the unsuitability of traditional TOBIT approaches where the concentration of DEA scores at 1 are wrongly taken as the result of a censoring mechanism (Simar and Wilson 2007).

[4] PISA evaluates students aged 15 and in Uruguay this is a cut-off age dividing lower and upper secondary education.

In the initial sample, those schools presenting non-zero values for the input and output variables reach 118 centers. These centers are selected to apply the DEA technique. Table 2 summarizes their main features:

Table 2. PISA 2015 sample

	Schools	Number	%
Sector	Public	82	69,5
	Private	36	30,5
Region	Montevideo	53	44,9
	Provinces	65	55,1
Cycle	Upper-Sec.	32	27,1
	Lower & Upper sec.	86	72,9
Total		118	100

Source: own estimation based on PISA 2015 Uruguay Database

Two output variables are used to describe the student achievement: the PISA marks at reading and mathematics. Their joint inclusion underscores the potential synergies between both majors in the production of an overall learning outcome. Competence at sciences is not included for it might be thought as a by-product of the proficiency at the two other fields. PISA provides 10 plausible values (PVs) for each student performance built upon distributions of the test scores. As in Agasisti (2013), the present study takes the average of the PVs at each knowledge field.

Before computing efficiency, following Equation (1) we untangle the student characteristics (matrix S_i) from the individual PISA achievement. The variables included in the matrix are sex, pre-primary education attendance, home possession, parental education and working conditions.[5] The last three are part of the PISA index of economic, social and cultural status (ESCS), which has often been employed either as an input or as a contextual variable in previous DEA analyses. Home possession is a PISA indicator used as a *proxy* for family wealth while sex and pre-primary education attendance have been proved to affect the academic outcomes of students in different tests (OECD 2016b). The indicators regarding mother's and father's education, which strongly impact the children performance, are considered separately. For each case, the variables express trade-offs respect to an omitted category: the illiterates.

The α coefficient estimated in Equation (1) requires one adjustment before taking it as an output. The coefficient stands for the effect of each of the schools on the PISA mathematics and reading scores, respectively, which are captured by a set of dummies. In order to get only positive values,

[5] Ideally, the explanatory variables should include information about the student's household composition and income, but these data are not available in the PISA records.

we set the school with the lowest coefficient as the reference and take all the other values in relation to this. This allows having only positive fixed school effects and one zero for the omitted school in the regression. In the rest of the paper, these school fixed effects are labeled as “PISA-adjusted scores”.

The DEA assumes that output efficiency is purely the result of how DMUs manage their controllable inputs. However, depending on the type of organization under analysis, the discussion about the controllable nature of inputs becomes a serious challenge. Schools provide a public service where the decisions on input allocation depend on the directives of public administration bodies: school principals are not totally free to dispose on the inputs they have to manage. In Uruguay this is true for all schools but holds a stronger effect on public schools. Based on these arguments, this paper considers as discretionary those inputs that schools necessary require to keep the every-day education process running. Also those so relevant that if demanded on the public authorities, they deserve an immediate solution. Conversely, those factors that depend on strategic or longer run decisions are considered as “non-discretionary”.

Hence, input variables in DEA comprise those basic factors that should be available to build a proper learning environment, e.g. teachers and infrastructure. To account for teachers, two measures are combined: the inverse of the student/teacher ratio provided by PISA, which reflects the intensity of the use of human resources (*teacher ratio*) and the share of those who hold a teaching certification (*cert*). We compute the following in order to correct the teacher endowment by a proxy of its qualification:

$$\textit{teacher ratio x (1+cert)} \qquad (4)$$

Regarding the school infrastructure, PISA provides an index of the quality of educational resources based on the principal’s perceptions about the availability of equipment, materials, computers, library and similar resources. The original answers are processed so that higher values of the index indicate a better quality of the educational resources (OECD 2013). The rationale to include this input is that, once a minimum level has been reached, it is the quality of resources more than their amount what really matters to affect education outcomes (OECD 2016a). In fact, it has been argued that after individuals are in school, the quality of school resources may influence student learning (Bacolod and Tobias 2006).

Table 3 contains the descriptive statistics for inputs and outputs.

Table 3. Descriptive statistics for inputs and outputs

Variable	Obs	Mean	Std. Dev.	Min	Max	Pairwise correlations Maths adj.	Read. adj.
			Outputs				
PISA Math. adjusted	118	84,93	35,85	10,45	203,68	----	----
PISA Read. adjusted	118	97,40	39,37	10,76	227,80	----	----
			Inputs				
Teach./students & certification	118	0,15	0,10	0,02	0,77	0,076	0,018
Quality Ed.Res. (index)	118	3,62	0,96	1,88	4,86	0,283	0,269

Source: own computation based on PISA 2015 Uruguay Database

There is a positive association between PISA records and the selected input, so that input increases are expected to yield output expansions. This picture gives support to a DEA input/output analysis. Based on it, schools are ranked according to their distance *vis-à-vis* an efficiency frontier, which represents the best performing units. A school is considered efficient whenever its input-output combination lies on the DEA frontier. Then, its output-oriented efficiency score would equal 1.[6]

Finally, we resort to a set of variables which might affect the efficiency performance but are not totally under the control of the school management. We consider two groups of factors: school structural characteristics (as school size, geographical location and private or public ownership) and learning environment. The latter is based on the school's principal perception about the supporting and administrative staff and the behavior of students and teachers.

Regarding the first group of variables, the school size is measured by the number of attending pupils. The expected efficiency effect of this variable is not clear: smaller schools may ease the integration among students, teachers and parents strengthening the learning community and promoting a better usage of the available educational resources. Conversely, larger schools have administrative economies of scale and may attract more experienced teachers. Besides, a greater diversity of students makes it easier for them to find peers sharing the same preferences (OECD 2016b). These aspects should probably have positive impacts on the educational outcomes leading to better efficiency results.

The geographical location of schools indicates if the school is located in Montevideo or in a province. Again, this variable has not a defined impact. On one side, schools in Montevideo would

[6] The efficiency score computation has been made in STATA. The peer and slack decomposition have been estimated by the Efficiency Measurement System software by Scheel (2000).

have a better access to a broader cultural environment, with more educational resources which could contribute to more efficient results. On the other, the range of teachers and pupils' engagement to schools when belonging to a smaller community could be outstanding, driving also efficient performances.

Finally, the idea that private schools would be more prone to achieve an efficient performance hinges upon their exposure to competence to attract pupils in order to survive. This would compel them to meet pupil's demands while combining a sound administration of resources with the search for education quality, a pressure far less present at public schools (Mancebón et al. 2012).

Considering the learning environment, PISA 2015 provides summary measures describing the extent to which the school principals think that education at the centre is "hindered" by a range of factors. This formulation is deemed to capture both how often the situation takes place at the school and how much it affects the student learning process (OECD 2016b).[7]Based on the original measures, we compound dummy variables to detect whether their presence might influence efficiency. Among all the possible variables, this paper has focused on those regarded as more relevant at the Uruguayan context (see Section 2): student attendance, teacher absenteeism, teachers not well prepared for classes, availability and qualification of non-teaching personnel.[8]

The expectation about these influences is that education outcomes for the given inputs are better as long as there is regularity in student and teacher attendance (that is, thereare fewer missed learning or teaching opportunities) and better teacher preparation of classes. Additionally, the availability and qualification of assisting staff entail a daily interaction and caring for students which should probably impact their learning experience leading to better efficiency results.

This set of variables is applied to compute the bootstrapped regression models suggested by Simar and Wilson (2007). The models are right truncated at the value of 1. They have been estimated by using with 1000 bootstrap replicates. Table 4 contains the descriptive statistics for these variables and briefly refers to their construction.

We must note that several human and material resource measures are based on the school principal perceptions provided by the PISA questionnaires. Thus, they do not express statistical information but opinions, which could be affected by the context in which the schools operate. They might be influenced by the principal's expectations about the best possible resources to be obtained or the worst possible behaviors which they use to come up with. The use of dummies seeks to summarize as much as possible the core views about these different aspects so to make them comparable across schools.

[7]In the original dataset, the responses are grouped into 4 categories from 1 to 4: "not at all"; "very little"; "to some extent" and "a lot", respectively (OECD 2016b).

[8]In secondary education, the non-teaching staff may comprise group leaders, pedagogical or counsellor teachers, psychologists, social workers and administrative personnel.

Table 4. Descriptive statistics for contextual variables

Variable	Definition	Obs.	Mean	Min	Max
School type (dummy)	=1 private schools; =0 public schools	118	0.31	0	1
School size(log)	number of students in the school	118	6.34	3.87	8.19
Region (dummy)	=1 for Montevideo; 0= Provinces	118	0.45	0	1
Shortage of non-teaching staff (dummy)	=1 if the principal's perception about this problem is that it matters "something" or "a lot".	118	0.64	0	1
Qualified assisting staff (dummy)	=1 if the principal's perception is that assisting staff is not poorly qualified	118	0.30	0	1
Teacher absenteeism (dummy)	=1 if the PISA indicator "extent to which student learning is hindered by teacher absenteeism" takes values 2 ("little"); 3 ("some") and 4 ("a lot").	118	0.87	0	1
Learning influenced by teachers not well prepared to classes (dummy)	=1 if the principal's perception about this problem is that it matters "to some extent" and "a lot".	118	0.73	0	1
Pupil absenteeism (dummy)	=1 if the PISA indicator "extent to which student learning is hindered by students skipping classes" takes values 3 ("to some extent") and 4 ("a lot").	118	0.33	0	1

5. Results

5.1 School fixed effects and DEA results

Table A.1 contains the estimates for PISA Mathematics and Reading scores used to obtain the corresponding school fixed effects. According to the results, home possessions and mother's and father's highest education levels have a significant positive role to explain individual PISA performances. Besides, girls are consistently better than boys at reading while the opposite happens for mathematics. Table A.2 shows the descriptive statistics for the raw PISA and the PISA-adjusted scores.

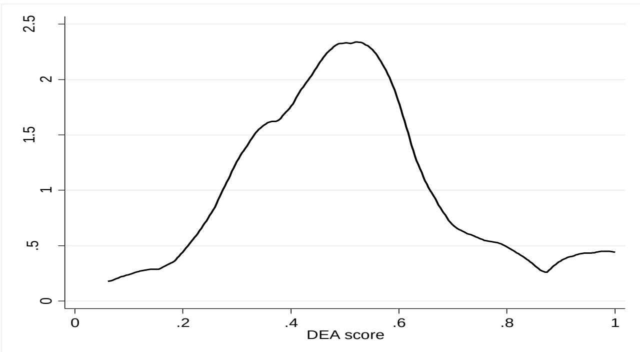
Table 5 presents the output- oriented DEA efficiency scores under VRS. The results show that seeking efficiency might exert an overall positive impact on student performance. The mean efficiency score is 0.52, indicating that the average school could improve outputs by 48% without changing inputs in order to operate at the efficiency frontier. Just 5% of schools are fully efficient, that is, they comply with an output achievement that is in line with their input use.

Table 5. Summary measures of DEA efficiency scores

Descriptive statistics	DEA score
Mean 1st quartile	0.29
Mean 2nd quartile	0.46
Average sample	0.52
Mean 3rd quartile	0.56
Mean 4th quartile	0.83
Share efficient schools	5%
Total schools	118

The score distribution has a concentration of mass in the middle values and quite long tails, suggesting a considerable dispersion in the efficiency attainments (Figure 1). There is also a slight accumulation at the upper tail of the distribution, indicating a considerable presence of quite efficient schools (scores higher than 0.85).

Figure 1. Efficiency score distribution

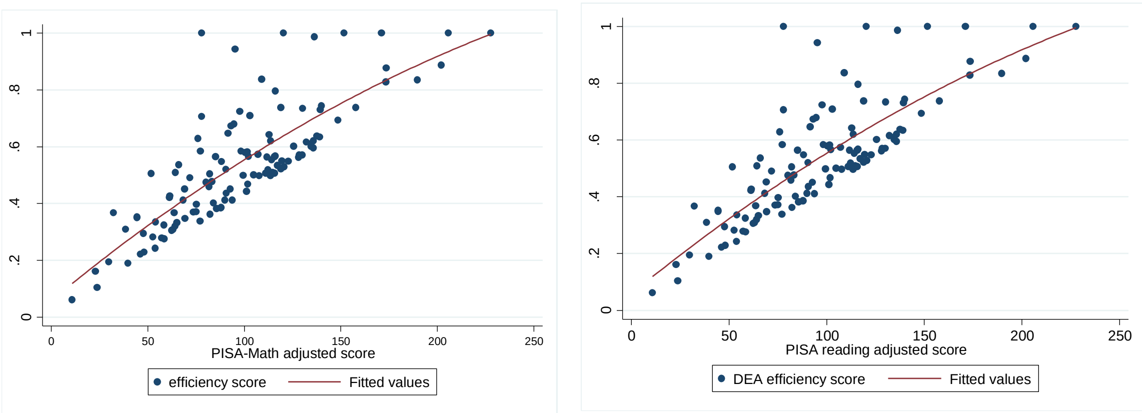


Source: own computation

The output measure based on an adjusted PISA score makes it difficult to net out the precise percentage points in which the raw test marks should be expanded to attain an optimal performance. However, they do point out to serious efficiency gaps: given the current resources, the average high-school has a considerable margin to attain better learning outcomes.

One relevant feature of the data is that PISA-adjusted performances and efficiency scores are correlated: it can be expected that the more efficient schools are the better education outcomes they get. However, this relationship is not linear, as shown in Figure 2 for Mathematics and Reading, respectively.

Figure 2. PISA adjusted marks and efficiency scores

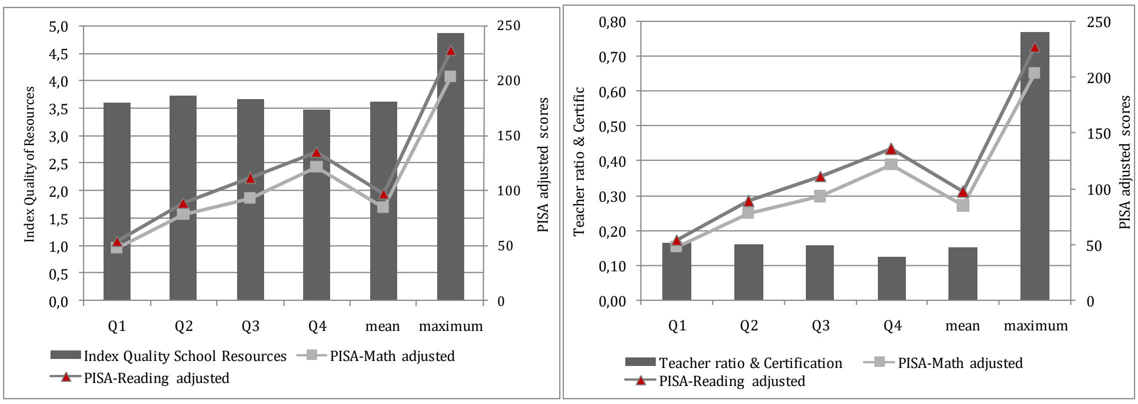


Source: own computation

Additionally, it is interesting to note whether there is any relationship between better educational outcomes and a richer input availability. For each input endowment (teacher or infrastructure), Figure 3 shows the output values together with the input allocation at the mean and maximum efficiency level and the 4 quartile sample values. According to panels (a) and (b), the PISA adjusted scores behave similarly and the range of differences in input endowments across quartiles does not seem to be outstanding for either input. The most efficient schools (Q4) present the highest PISA adjusted scores, a result attained bearing an input endowment which is not only below the one for the average efficiency level but also below the mean of the rest of the quartiles. In general, the most efficient schools seem to be those with the highest PISA records and the lowest input endowment.

Figure 3. Input endowment according to efficiency distribution measures

(a) Input 1: Index of Quality of School Resources; (b) Input 2: teacher/student & certification



Source: own computation

The performance of the schools in the 1st quartile (those which should expand outputs 71% to achieve efficiency) provides more insight into the efficiency patterns. Figure 4 in panel (a) allows checking that, on average, peers or benchmark units (colored in black) share a similar input endowment with the most inefficient ones. However, their output achievement is clearly superior. The three benchmarks identified for the units in the 1st quartile are private schools. The underlying message is twofold: first, under the current input use, a better output level seems to be an attainable aim and second, just seeking efficiency would accrue very important output improvements.

Figure 4. Panel (a) Input endowment of schools in 1st efficiency quartile *vis-à-vis* their peers

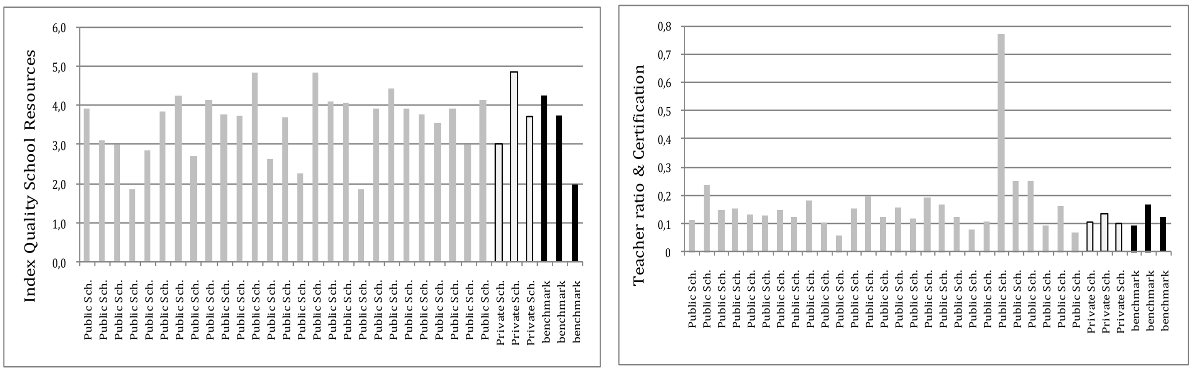
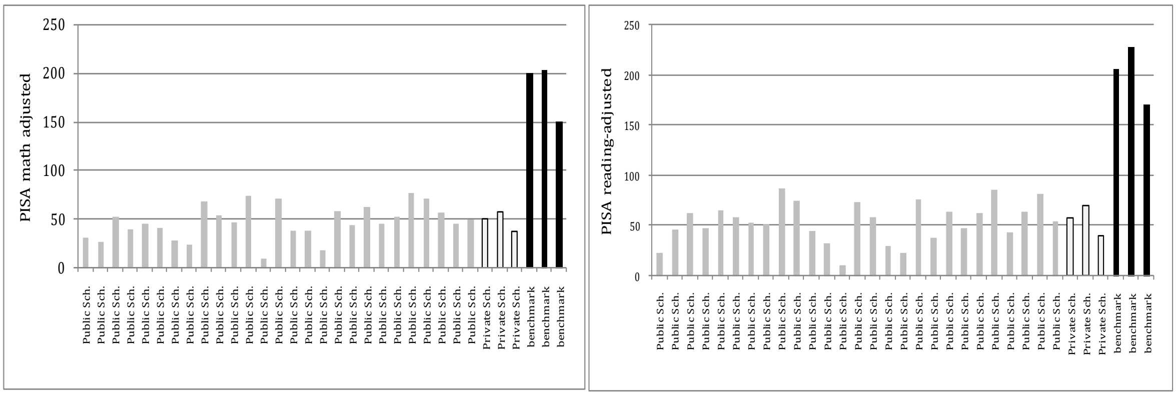


Figure 4. Panel (b) Output of schools in 1stefficiency quartile *vis-à-vis* their peers



Source: own computation

Moreover, the output slack computation for the schools of the 1st quartile indicates whether there is still room for efficiency gains even after the average 71% improvement in both outputs has been performed. According to results, all schools should have to take output improvements further even after the overall efficiency correction has taken place: in 57% of cases, the focus should be on the Mathematics achievement (Figure A.1).

Among the least efficient schools (Q1 and Q2), most are public, situated in provinces and operating the complete secondary cycle. Within the most efficient group, the picture changes: first, Montevideo becomes the preferred location. Second, efficiency gains are associated to a more balanced distribution between public and private school types, particularly among the most efficient schools. This last result points out two important facts: on one hand, private schools make headway among the most efficient group, though they do not prevail. On the other, it seems that after a fair effort the group of public schools in the 4th quartile is perfectly capable of attaining efficiency. That is in deep contrast with the condition of the rest of public schools, which are governed under the same rules and where public funds are very far from being used in an efficient way.

Complete cycle schools are also a majority among the most efficient ones, but their presence diminishes (Table 6).

Table 6. Efficiency quartile composition by region, cycle and school type

Schools		Q1	Q2	Q3	Q4
Region	Montevideo	13.0	28.0	53.0	83.0
	Provinces	87.0	72.0	47.0	17.0
Cycle	Upper-Sec.	12.0	14.0	33.0	38.0
	Lower & Upper sec.	88.0	86.0	67.0	62.0
Sector	Public	90.0	69.0	67.0	52.0
	Private	10.0	31.0	33.3	48.3

Source: own computation

A closer look at the efficiency performance of private and public schools shows that both types are quite evenly represented in the central quartiles. However, private schools are more concentrated in the 4th efficiency quartile and public schools in the 1st one (Table 7). Together with data from Table 2, the information of Table 3 seems to indicate an efficiency advantage of private schools.

Table 7. School type distribution across efficiency quartiles

Efficiency quartiles	Private Schools	Public Schools
Q4	38.9	18.3
Q3	27.8	24.4
Q2	25.0	24.4
Q1	8.3	32.9
Total	100.0	100.0

Source: own computation

When input data are considered, the distinction between school types within each quartile indicates that both input endowments are higher for private than public schools. The largest difference corresponds to the teacher input in the 1st quartile: there the input measure in private schools is more than 3 times the one in public schools. In the rest of cases, the gaps persist in a range of 40-50% in favor of private schools (Table 8). Therefore, the input endowment in public schools is consistently poorer than in private institutions. However, the main concern in the present efficiency discussion point out to the failure in using the available resources at their maximum capability. Such a shortcoming prevails regardless the actual school input level.

Table 8. Input endowment by school type across efficiency quartiles

Efficiency Quartiles	Q1		Q2		Q3		Q4	
Inputs	T. ratio & Certif.	I. Q. Ed. Res.	T. ratio & Certif.	I. Q. Ed. Res.	T. ratio & Certif.	I. Q. Ed. Res.	T. ratio & Certif.	I. Q. Ed. Res.
Average	0.16	3.61	0.16	3.74	0.16	3.66	0.13	3.48
Ave. Priv. Schools	0.42	3.88	0.18	4.38	0.20	4.55	0.15	4.06
Ave. PublicSchools	0.13	3.58	0.15	3.44	0.13	3.21	0.10	2.94

Source: own computation

Given the variability of output expansions needed to enhance the efficiency of schools, it is important to understand how additional factors other than inputs condition the achievement of an optimal performance.

5.2. Environmental factors accounting for efficiency

Table 9 reports the estimates of Equation (3) using bootstrapped truncated regressions. Column (1) indicates that efficiency is higher in private than in public schools and in Montevideo over the provinces. Also, efficiency gains are higher as schools are larger. All coefficients are highly significant. Results about better efficiency results being associated to private schools are in line with what expected. Being in the capital city, with a broader access to cultural resources and infrastructure seems to be a positive factor. The same happens with the school size: bigger schools, which attract more experienced teachers and student diversity seems to build economies of scale easing the way towards efficiency.

These baseline results about school structural characteristics remain unchanged across Columns (2) to (5), which gradually add-up new controls. Column (2) includes the characteristics of the non-teaching staff. It shows the significant efficiency gains from the principal's perception about the adequate expertise of the assisting staff together with the negative impact of its shortage, though this last feature is significant at a lower level. Alternatively, Column (3) considers teacher behavior: absenteeism and deficit in class preparation. Against what could be expected, once controlled for the baseline variables, efficiency is not affected by these teacher characteristics, despite being reported as a prime concern for school principals. Column (4) combines Column (2) and (3) estimates yielding the same results. Finally, Column (5) shows the most complete specification adding the perceived student regular absenteeism, which does not bear any efficiency effect.

Table 9. Efficiency determinants

Dep.var: efficiency score	(1)	(2)	(3)	(4)	(5)
School type	0.138***	0.125**	0.156***	0.146***	0.137***
	(0.044)	(0.050)	(0.047)	(0.049)	(0.050)
School size (log)	0.0685***	0.0596***	0.064***	0.0531**	0.0536***
	(0.021)	(0.020)	(0.021)	(0.021)	(0.020)
Region	0.117***	0.145***	0.120***	0.150***	0.154***
	(0.037)	(0.038)	(0.039)	(0.038)	(0.036)
Qualified assisting staff		0.132***		0.137***	0.136***
		(0.033)		(0.035)	(0.035)
Shortage of non-teaching staff		-0.062*		-0.073*	-0.074*
		(0.039)		(0.041)	(0.043)
Teacher absenteeism			0.016	0.034	0.032
			(0.048)	(0.047)	(0.046)
Teachers not well prepared			0.032	0.038	0.045
			(0.040)	(0.038)	(0.038)
Pupil absenteeism					-0.028
					(0.035)
Constant	-0.020	0.0258	-0.0342	0.005	0.010
	(0.134)	(0.135)	(0.131)	(0.130)	(0.123)
Observations	118	118	118	118	118

*** p<0.01, ** p<0.05, * p<0.1; standard errors in parenthesis
Note: school type is 1=private; 0= public; region =1 is Montevideo; 0= provinces; qualified assisting staff=1; other=0; shortage of non-teaching personnel =1; other=0; pupil absenteeism =1, other =0; shortage of non-teaching staff =1; other=0; teacher absenteeism implies a problem=1; 0 other; teachers not well prepared=1 if the principal's perception about this problem is that it matters "to some extent" and "a lot"; other=0.

In the above table, there is a possibility that the school type variable hides the efficiency effects related to teacher behavior. For this reason, estimates in Column (2) and (5) of Table 9 are replicated in Table 10 ruling out the effect of the school type. The results are similar to those previously obtained: perceptions about teaching performance do not have any efficiency implication. Just the student absenteeism appears with a negative and statistically significant impact on efficiency.

Table 10. Efficiency determinants excluding the school type

Dep.var: efficiency score	(1)	(2)
School size (log)	0.034**	0.035*
	(0.018)	(0.020)
Region	0.205***	0.208***
	(0.033)	(0.032)
Qualified assisting staff	0.134***	0.134***
	(0.036)	(0.035)
Shortage of non-teaching staff	-0.103***	-0.106***
	(0.038)	(0.041)
Pupil absenteeism		-0.057*
		(0.035)
Teacher absenteeism		0.016
		(0.049)
Teachers not well prepared		0.022
		(0.041)
Constant	0.227**	0.208**
	(0.101)	(0.104)
Observations	118	118

In the alternative regressions of Table 10, the variables keep their sign, but there is some impact on their size. The efficiency effects are larger for region and shortage of non-teaching staff. In this last case, the statistical significance of the coefficient is also higher. Hence, it seems that the school type in Table 9 mainly collides with the availability of non-teaching personnel not with its qualification. The constant also increases its magnitude and significance. This would imply that the exclusion of the school type variable leaves relevant efficiency drivers unexplained.

Table 11 presents some robustness checks on the complete specification, with and without school type: Columns (1) -(3) and (4) -(6), respectively. In Columns (1) and (4) the number of bootstrap replications has been changed from 1000 to 2000. This modification does not alter the obtained results. The Columns (2) and (5) check whether complete-cycle schools hold any incidence on efficiency.

Table 11. Robustness checks

Dep.var: efficiency score	(1)	(2)	(3)	(4)	(5)	(6)
School type	0.137***	0.151***	0.129***			
	(0.049)	(0.050)	(0.050)			
School size (log)	0.054***	0.046**	0.051***	0.035*	0.032	0.033*
	(0.020)	(0.021)	(0.019)	(0.019)	(0.020)	(0.018)
Region	0.154***	0.144***	0.162***	0.208***	0.207***	0.214***
	(0.036)	(0.038)	(0.036)	(0.033)	(0.035)	(0.032)
Qualified assisting staff	0.136***	0.140***	0.140***	0.134***	0.135***	0.139***
	(0.033)	(0.034)	(0.033)	(0.036)	(0.036)	(0.035)
Shortage of non-teaching staff	-0.074*	-0.070*	-0.074*	-0.106**	-0.106**	-0.104***
	(0.041)	(0.040)	(0.041)	(0.041)	(0.041)	(0.038)
Teacher absenteeism	0.032	0.038	0.030	0.016	0.017	0.014
	(0.046)	(0.047)	(0.046)	(0.050)	(0.049)	(0.049)
Teachers not well prepared	0.045	0.049	0.046	0.022	0.023	0.025
	(0.039)	(0.038)	(0.037)	(0.043)	(0.042)	(0.039)
Pupil absenteeism	-0.028	-0.027	-0.025	-0.057*	-0.058*	
	(0.035)	(0.035)	(0.034)	(0.036)	(0.036)	
Complete cycle schools		-0.057*			-0.020	
		(0.035)			(0.035)	
Use of standardized tests			0.048*			0.056*
			(0.030)			(0.032)
Constant	0.010	0.088	0.011	0.208**	0.242*	0.196**
	(0.124)	(0.131)	(0.126)	(0.105)	(0.125)	(0.099)
Observations	118	118	118	118	118	118

There might be efficiency reductions at schools operating the complete cycle, but the statistical significance of the impact is visible just in one specification. The use of standardized test emerges as a statistically positive influence for efficiency at both specifications (Columns 3 and 6). This is an interesting issue because, once controlled for variables associated to structure and learning environment, the fact that students might be more used to standardized assessments similar to PISA, enhances the outcomes. This "training-effect" is not limited to private schools, as it also appears after school type has been controlled for.

6. Concluding remarks

Based on PISA data, we evaluate efficiency differences within a sample of Uruguayan high-schools and discuss which factors might push them towards a better resource use. The analysis relies on a non-parametric technique (DEA) followed by bootstrapped truncated regressions. A particular focus is made on comparing school level data removing student features, on discussing a defined set of context variables and on assessing private and public school achievements.

After correcting the PISA scores, we find that the school average DEA score exhibits a quite modest efficiency level. Given the current resources, the average school could expand their educational outcomes 48% to attain an optimal performance. School efficiency seems to be related to the PISA performance: the more efficient schools are the higher outputs they get. However, the relationship tends to lose strength for the higher PISA scores, both in mathematics and reading. In opposition, the efficiency achievements are not compatible with the school input endowment. Despite the similar input use across the sample, the least efficient schools should improve outputs in 70% to attain efficiency, while the effort in the most efficient ones implies a 17% of expansion. The most problematic situation appears in public schools which are the largest part of the least efficient units.

The results show that structural features, as the private school ownership, a bigger size and being located in the capital city are significantly associated to efficiency gains. Once controlled for this set of influences, the availability and qualification of the non-teaching staff are also relevant efficiency drivers. The negative effect of student absenteeism is just revealed when the regressions exclude the school type variable. This would suggest that this sort of student behavior could be behind the differences between private and public schools. The only aspect related to teaching practices is the positive effect of using standardized tests, which could probably be more associated to a general directive at the school level than to any single teacher impulse.

Among all explanatory variables, the less straightforward interpretation refers to the private school ownership. After controlling for the student background, the teaching and not-teaching staff features, region and school size, there are still some characteristics in how private schools run the available resources that positively impacts efficiency. The fact that under a fair performance comparison private are more capable than public schools to extract the maximum output from their inputs points out to deficits in the idiosyncratic characteristics of the way public schools are managed.

7. Bibliography

Afonso, A. and St. Aubyn, M. 2006. Cross-country efficiency of secondary education provision: a semi-parametric analysis with non-discretionary inputs". Economic Modelling, 23 (3): 476-491.

Afonso, A., Schuknecht. L. and Tanzi, V. 2010. Public sector efficiency: evidence for new EU member states and emerging markets. Applied Economics, 42 (17): 2147-2164.

Agasisti, T. and Zoido, P. 2015. The efficiency of secondary schools in an international perspective: preliminary results from PISA 2012. OECD Education Working Paper 117.

----------- 2013. The efficiency of Italian secondary schools and the potential role of competition: a data envelopment analysis using OECD-PISA 2006 data. EducationEconomics 21 (5): 520-544.

ANEP 2017. Uruguay en PISA 2015. Informe de resultados. Administración Nacional de Educación Pública. Consejo Directiva Central. División de Investigación, Evaluación y Estadística, Programa PISA Uruguay.

Banker, R. D., Charnes, A. and Cooper, W. 1984. Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management Science*:* 1078- 1092.

Bacolod, M. and Tobias, J. 2006. Schools, school quality and achievement growth: evidence from the Philippines. Economics of Education Review 25 (6): 619-632.

Calero, J. and Escaríbul, J.O. 2007. Evaluación de servicios educativos: el rendimiento en los centros públicos y privados medido en PISA 2003. Hacienda PúblicaEspañola 183(4): 33-66.

Charnes, A., Cooper, W. and Rhodes, E. 1978. Measuring the Efficiency of Decision Making Units. European Journal of Operational Research 2: 429–444.

Crespo E., Pedraja F. and Santín D. 2014. Does school ownership matter? An unbiased efficiency comparison for regions of Spain. Journal of Productivity Analysis 41(1):153–172

Coleman, J., Campbell, E., Hobson, C. 1966. Equality of Educational Opportunity, U.S. Department on H.E.W Office of Educational, Washington, D.C.

Doneschi, A. 2017. Desigualdad de aprendizajes en Uruguay: determinantes de los resultados de PISA 2012. Documentos de Trabajo 1/17 DECON, Facultad de Ciencias Sociales, UdelaR.

Johnes, J. 2015. Operational research in education. European Journal of Operational Research 243, 683-696.

Haelermans, C. and Ruggiero, J. 2013. Estimating technical and allocative efficiency in the public sector: A nonparametric analysis of Dutch schools. European Journal of Operational Research, 227, 174-181.

Hanushek, E. 2003. The failure of input-based schooling policies. The Economic Journal, 113: F64-F98.

----------- 1979. Conceptual and empirical issues in the estimation of educational production functions. Journal of Human Resources 14 (3): 351-388.

Farrell, M. 1957. The measurement of productive efficiency. Journal of the Royal Statistical Society, Series A 120, Part 3: 253-290.

Filgueira, C. and Lamas, C. 2005. Gestión en los centros de enseñanza secundaria de MontevideoAdministración Nacional de Educación Pública ANEP, Montevideo.

International Monetary Fund. 2014. IMF Policy Paper: Fiscal policy and income inequality. IMF, Washington D.C.

INEEd. 2017. Informe sobre el estado de la educación en Uruguay 2015-2016, Instituto Nacional de Evaluación Educativa, Montevideo.

-----------. 2014. Informe sobre el estado de la educación en Uruguay 2014, Instituto Nacional de Evaluación Educativa, Montevideo.

Hanusek, E. and Woessmann, L. 2012. Schooling, educational achievement, and the Latin American growth puzzle. Journal of Development Economics 99: 497-512.

Llambí, C. and Perera, M. 2009. La Función de Producción Educativa: el posible sesgo en la estimación de efectos "institucionales" con los datos PISA. El caso de las escuelas de Tiempo Completo, Documento Trabajo 03/2009, CINVE, Montevideo.

Mancebón, M., Calero, J., Choi, A. y Ximénez de Embún, D.P. 2012. Efficiency of Public and Publicly-Subsidised High Schools in Spain. Evidence from PISA 2006. Journal of Operational Research Society 63: 1516-1533.

Mancebón, M. and Muñiz, M. 2008. Private versus private high schools in Spain: disentangling managerial and programme efficiencies. The Journal of the Operational Research Society 59(7): 892-901.

McDonald, J. 2009. Using least squares and Tobit in second stage DEA efficiency analyses. European Journal of Operational Research, 197(2):792 -798.

Naper, L. 2010. Teaching hiring practices and educational efficiency. Economics of Education Review 29: 658-668.

Nghiem, S. and Nguyen, H. and Connelly, L. 2016. The efficiency of Australian schools: a nationwide analysis using gains in test scores of students as outputs. Economic Papers, 35(3): 256-268.

OECD. 2017. Country note. Programme for International Student Assessment (PISA). Results from PISA 2015. OECD Publishing, Paris.

OECD. 2016a. PISA 2015 Results (Volume I): Excellence and Equity in Education, PISA, OECD Publishing, Paris.

OECD 2016b. PISA 2015 Results (Volume II): Policies and Practices for Successful Schools, PISA, OECD Publishing, Paris.

OECD. 2013. PISA 2012 Results: What Makes Schools Successful: Resources, Policies and Practices. OECD Publishing, Paris.

Perelman, S. and Santin, D. 2011. Measuring educational efficiency at student level with parametric stochastic distance functions: an application to Spanish PISA results. Education Economics, 19(1): 29-49.

Portela, M., Camanho, A. and Borges, D. 2012. Performance assessment of secondary schools: the snapshot of a country taken by DEA. The Journal of the Operational Research Society 63(8): 1098-1115.

Portela, S. and Thanassoulis, E. 2001. Decomposing school and school type efficiency. European Journal of Operational Research 132: 357-373.

Ramanathan, R. 2003. An introduction to Data Envelopment Analysis. A tool for performance measurement. Sage Publications, India.

Santiago, P., Ávalos, B., Burns, T., Morduchowicz, A. and Radinger, T. 2016.Reviews of School Resources: Uruguay 2016. OECD Publishing, Paris.

Santin, D. and Sicilia, G. 2015. Measuring the efficiency of public schools in Uruguay: main drivers and policy implications. Latin American Economic Review (2015) 24:5.

Scheel, H. 2000.EMS: Efficiency Measurement System User's Manual. Version 1.3.

Schwellnus, C. 2009. Achieving higher performance: enhancing spending efficiency in health and education in Mexico. OECD Economics Department Working Paper 732.

Simar, L. and Wilson, P. 2011. Two-stage DEA: caveat emptor. Journal of Productivity Analysis, 36: 205-218.

----------- 2007. Estimation and inference in two-stage, semi-parametric models of production processes. Journal of Econometrics, 136 (1): 31-64.

Thieme, C., Prior, D. and E. Tortosa. 2013. A multilevel decomposition of school performance using robust nonparametric frontier techniques. Economics of Education Review 32: 104-112.

Appendix

Table A.1. Determinants of student performance, 2015

Dep. variable: individual PISA score	PISA Mathematics	PISA Reading
Sex (1=girl)	-18.23***	18.71***
	[8.49e-11]	[2.95e-09]
Home possessions Index	8.322***	8.108***
	[2.02e-05]	[0.000253]
Attendance to pre-primary education	2.238	-4.156
	[0.707]	[0.569]
Mother's highest educ. is primary	18.13*	14.93
	[0.0579]	[0.105]
Mother's highest educ. is lower sec./technique	15.58	6.376
	[0.112]	[0.505]
Mother's highest educ. tech. sec. complete	34.39**	0.212
	[0.0272]	[0.989]
Mother's highest educ. is upper sec.	25.59***	17.18*
	[0.00812]	[0.0708]
Mother's highest educ. is tertiary	13.43	16.00
	[0.199]	[0.121]
Mother's highest educ. is complete univ.	21.90**	15.46
	[0.0301]	[0.124]
Father's highest educ. is primary	0.427	1.708
	[0.957]	[0.846]
Father's highest educ. is lower sec./technique	5.666	5.962
	[0.472]	[0.499]
Father's highest educ. tech. sec. complete	8.059	2.885
	[0.479]	[0.811]
Father's highest educ. is upper sec.	5.422	10.81
	[0.499]	[0.226]
Father's highest educ. is tertiary	18.72**	22.60**
	[0.0349]	[0.0234]
Father's highest educ. is complete univ.	14.41*	12.55
	[0.0932]	[0.192]
Mother currently working	3.644	6.651
	[0.352]	[0.134]
Father currently working	-5.284	-5.767
	[0.478]	[0.453]
Constant	360.8***	361.4***
	[0]	[0]
School fixed effect	yes	yes
Observations	2,786	2,786
R-squared	0.426	0.373

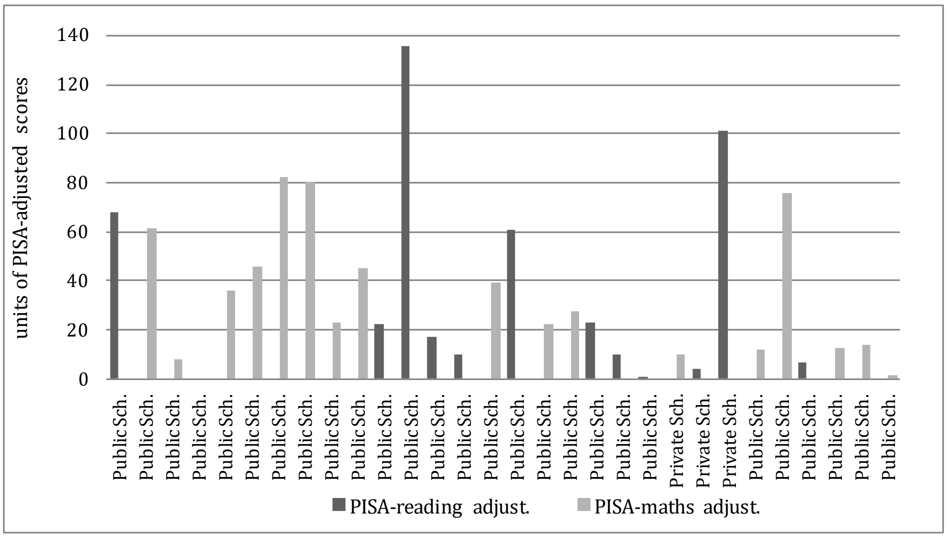
*** $p<0.01$, ** $p<0.05$, * $p<0.1$; t-values in parenthesis.

Table A.2. Descriptive measures of original and adjusted PISA scores

Variable	Obs	Mean	Std. Dev.	Min	Max
PISA Reading	118	483.7	43.7	398.6	622.6
PISA Math.	118	457.5	42.9	374.5	596.6
PISA Read. Adjusted	118	97.4	39.4	10.8	227.8
PISA Maths Adjusted	118	84.9	35.8	10.4	203.7

Source: based on PISA 2015 Uruguay Database

Figure A.1. Outputs slacks (in units of PISA-adjusted scores)



Source: own estimation

INSTITUTO DE ECONOMÍA

Serie Documentos de Trabajo

Diciembre, 2018

DT 14/2018

Instituto de Economía

Facultad de Ciencias Económicas y de Administración

Universidad de la República - Uruguay