Public and private school efficiency and equity in Latin America: new evidence based on PISA for development

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Public and Private School Efficiency and Equity in Latin America: New Evidence Based on PISA for Development

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Abstract

Using the recent PISA for Development (2017) learning survey, we offer new evidence on whether there is a private-public schools efficiency gap in Latin America and the role of distinct barriers and inequality on efficiency. We obtain school efficiency scores using Data Envelopment Analysis from 705 schools in four countries –Ecuador, Guatemala, Honduras and Paraguay. We find that the private schools efficiency is 0.88 whereas it is lower for public schools (at 0.82). Thus, there is a positive efficiency gap for private schools, with the lower efficiency in public schools may be explained by the additional obstacles they face (such as higher prevalence of student work). However, there is a greater scope in public schools of boosting efficiency by decreasing inequality and the provision of remedial classes. Whole sample results seems to be driven by two countries: Ecuador and Paraguay.

Keywords: data envelopment analysis, efficiency, equity, private-public learning gap, Latin America, PISA-D

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1. Introduction

In spite of the increasing inequality and segregation associated with the expansion of private schooling (Elacqua et al. 2016; Östh et al. 2013), Latin America has shown a growing trend in the participation of private enrolment at secondary level over the last two decades, reaching 19.1% in 2018 and being just slightly below sub-Saharan Africa where this participation is 20.6%.[1] Although this rate has stabilised in recent years, it has been playing an increasing role in expansion of school enrollment in the region (Elacqua et al. 2018). There is, however, a great disparity in the importance of the private sector across the LA region, with private secondary schools having in 2017 a participation of around 11.4% in Uruguay and 13.7% in Brazil, to 26.1% in Honduras and Ecuador to 63.4% in Guatemala and 61.9% in Chile,[2] showing the contextual character in which the process of expansion has developed in the region. The growth of the educational offer in the private sector has been carried out in tandem with the public education sector, giving rise to a mixed system where privately-managed and self-financed institutions coexist with state contribution and public institutions. This process has molded hybrid education systems in which the two sectors interact and distribute responsibilities in a complex and often contradictory manner (Verger et al. 2018).

Notwithstanding an expansion of education privatisation in Latin America (henceforth denoted as LA), the literature focusing on the phenomenon of school type efficiency is still limited (even more so from a regional perspective which requires a cross-country comparable survey), as well as the implications that the configuration of education systems in the region has on inequality. Hence, this paper fills this gap by acknowledging the dual nature of LA education systems and estimating private schools and public schools sub-equilibriums from an efficiency perspective. The hybrid or dual nature of financially constrained education systems from the global south and their related sub-equilibriums is not new and exclusive to the LA region. In the SSA region, for instance, Spaull (2013) finds that a dual nature of the education system in South Africa and a bimodal educational performance where the process which converts inputs into outputs is fundamentally different for each sub-system. Moreover, because some private education institutions are partially publicly funded, knowing whether governments' allocation of resources towards the private sector is both economically and equality efficient, is critical.

In this paper, therefore, we present new empirical evidence on private and public schools efficiency relying on a comparable cross-country learning survey (i.e., PISA for Development/PISA-D, 2017) for lower-and middle income (LMIC) countries. Importantly, PISA-D is designed to capture student's achievement at the bottom of the learning distribution and their specific social and economic contexts. Our analysis covers four LA countries (i.e., Ecuador, Guatemala, Honduras and Paraguay). Methodologically, we use Data Envelopment Analysis (DEA) (Thanassoulis 2001) which mimics an education production function where school inputs are transformed into outputs (Hanushek and Woessmann 2011) to estimate efficiency score of 705 schools (out of which 207 private schools and 498 are public schools). In its formulation, DEA allows us to control for key inputs such as family socioeconomic status (SES) and key school inputs driving selectively and self-selection into private schools, a commonly feature of regression analysis on the school type learning gap (e.g., Delprato and Chudgar 2018; de Oliveira et al. 2013; Vandenberghe and Robin 2004).

We expand the literature in different ways. Firstly, we present novel evidence on technical efficiency by school type based on tests (cognitive) scores alongside their determinants for the LA region, extending findings from developed countries (Agasisti and Zoido 2018; Sutherland et al. 2009). Secondly, we assess the efficiency-equity trade off by school type which is particularly important for the public sector in the context of expanding enrolment at secondary level in the region. The analysis draws on recent bootstrap methods yielding bias-correct estimates of efficiency scores (Simar and Wilson 2007; Badunenko and Tauchmann 2019). Ultimately, the new evidence contained in the paper contributes to the school type efficiency literature which tends to find mixed results across different settings (see review of Section 2).

The rest of the paper is organised as follows. The next section presents a brief background review on the subject of efficiency in education with a focus on the LA region. In Sections 3 and 4 we present the data and methodology employed. Section 5 contains the empirical findings. Finally, the paper ends with some concluding remarks in the last section.

2. Literature review of school type efficiency

One of the issues that has caught the attention of researchers working on studies measuring efficiency in educational institutions has been whether there are differences between public and private managed institutions. Studies have been carried out for different educational levels in various countries and regions (for details, see the literature review of De Witte and López-Torres 2017).

The empirical findings from private-public efficiency studies vary according to the educational level and context analysed. At the higher education level, Agasisti and Ricca (2016) carry out a comparative analysis of the efficiency of public and private universities in Italy. Their analysis is based on the DEA methodology for the period 2007-2011 and it uses as inputs the number of students and staff at the university and as outputs, the number of graduates and the income generated from scientific research. Among the two leading results, they find evidence that private universities are more efficient than public ones (between 7%-10% across years) being able to produce more educational and research outputs with the same (or lower) level of inputs, and also another key driver of efficiency is the geographical area of universities. Cordero Ferrera et al. (2010) using the PISA (2006) data and the DEA methodology at the student level, estimate regional efficiency levels in Spain. They find that students who attend private schools have lower levels of efficiency than those attending public schools and, additionally, they find a lack of support for the impact that school and classroom sizes have on students' efficiency. Using DEA and the same dataset for Spain, Mancebón et al. (2012) decompose the inefficiency between students and the structural differences in the two management/school types. They find that, once differences in students' backgrounds, school resources and individual management inefficiencies are removed, there are higher levels of efficiency in public high schools than in subsidised private schools.

Moreover, also at the secondary level, Alexander et al. (2010) also work with the two-stage DEA methodology to estimate relative efficiency in New Zealand secondary schools. In this study, the authors find evidence of a 8% positive gap on efficiency of private schools over public schools, suggesting that schools management practices used in the private sector could pay dividends for state schools. Perhaps surprisingly they do not find that socio-economic deprivation is negatively related to efficiency. Based on a somewhat different analysis at the student level, Cherchye et al. (2010) use DEA to compare the efficiency between public and private primary schools in Flanders, which has a system characterised by public and private schools fully funded by the state. They find that initial efficiency dominance of private schools over public schools disappears when accounting for the diverging environmental characteristics of pupil populations as well as equity, making any school type efficiency comparison based on uncorrected efficiency scores, misleading.

Focusing on country studies from the Latin America region, Mizala et al. (2002) assess the technical efficiency of primary schools in Chile using Stochastic Frontier Analysis (SFA) and DEA, differentiating between paid private, subsidised and municipal private establishments. Based on DEA, they find an average efficiency of the whole education system of 95% (though with a wide range or great dispersion on school efficiency varying from 53% to 100%). When efficiency is analysed for the three school types, the efficiency ranking they obtain is that private fee-paying schools are the most efficient, followed by private subsidised and public schools; in other words, they find that in Chile private institutions without subsidies are more efficient than the rest. However, they also find that in some cases efficiency is not fully correlated with the scores of some schools that, despite being efficient, don't achieve good results in standardised tests.

Equally, for Argentina using the same two efficiency techniques (i.e., SFA and DEA) and also for primary schools, Vera et al. 2011 obtain higher levels of efficiency in privately managed schools even after comparing private and public schools in equivalent environments. In an earlier related paper, also for Argentina, Vera et al. (2008) use data from the 2000 National Evaluation Operation to estimate the efficiency of primary schools using SFA. The results showed that a school's socioeconomic level, whether it is privately managed, its location (urban-rural location and its region within the country) are important determinants of primary schools efficiency. However, when controlling for socioeconomic level and other environmental variables, the initial differences in the efficiency levels between private and public schools substantially decreases. The authors argue that better quality inputs at private schools (e.g., having student coming from more affluent backgrounds) and a more efficient management of schools resources, place private schools in efficiency privileged positions in comparison to public schools. Similarly, Iregui-Bohórquez et al. (2006) use the stochastic frontier method to estimate the efficiency in more than 4,000 Colombian schools (using 2002 data). They identify raw differences in the efficiency levels of public and private schools, but again this gap disappears when controlling for differences on school environments.

From a LA regional perspective, Antequera (2019) runs a comparative analysis estimating the relative technical efficiency for schools in eight South American countries with two types of modeling (at the student and school levels) in the DEA methodology, based on the TERCE learning survey (primary level). In this study, no significant differences were found in the efficiency levels of public and private schools when working with the school as a decision-making unit (except in the case of Paraguay and for the output based on math scores). However, in the second type of DEA analysis where students are used as the optimising decision unit, the author finds statistically significant differences between private and public efficiency levels for some South American countries; that is, for Argentina, Chile and Uruguay (math) and Argentina, Paraguay, and Uruguay (reading). In a recent study, also for low-middle income countries, Johnes and Virmani (2020) use data from the Young Lives study (Ethiopia, India, Peru and Vietnam) to evaluate the efficiency of their education systems. The focus of their analysis is on the relative efficiency of each country through the estimation of a meta-frontier variant of data envelopment analysis, and to evaluate the impact of public and private schooling and of urban and rural location. Here, estimates indicate there are no differences in efficiency by school type in all cases, with rural schools mostly showing higher levels of efficiency.

Furthermore, also from an international perspective but for OECD countries, Agasisti and Zoido (2018) analyse the technical efficiency of secondary schools using a sample of 30 countries from PISA (2012) data including 8,500 schools. Their estimates show an overall degree of inefficiency of 27% (as the international efficiency frontier estimate is 0.73), with a varying degree of inefficiency varies across countries (e.g., from 15% in Singapore to 33% in Slovenia). As regards the private-public efficiency gap, however, they find a small and marginal negative gap given by the coefficient of the private school dummy in comparison to other determinants of efficiency.

All in all, this brief review supports the validity of different hypotheses and dissimilar empirical results for the private-public efficiency gap. Depending on the country, educational level considered and the database and methodology employed, findings range from a greater efficiency of some of the types of school, to a lack of statistical difference between their efficiency levels. Thus, the analysis of school efficiency by school type is still an area where new evidence can shed light onto specific sectorial issues, in particular for the education system of lower-and middle income countries.

3. Data

The analysis is based on the PISA for Development (PISA-D) learning surveys (2017). The survey consists of students at grade 7 (15 years old) or above from seven low and middle income countries. Our working sample includes four Latin

American countries: Ecuador, Guatemala, Honduras and Paraguay. Using the purchasing power parity for the year 2019, the countries from the LA working sample are not homogeneous based on GDP levels (per capita). Specifically, Honduras is the country with the lowest level of GDP, closely followed by Nicaragua. Then, there is Guatemala with GDP level similar to those of Bolivia or El Salvador; while there is a slightly higher GDP for Ecuador and Paraguay (with similar levels to each other). Within our sample, therefore, the extremes are shown by Honduras and Paraguay with the GDP of Honduras nearly half (≈45%) in comparison to Paraguay's. However, it should be noted that Paraguay's GDP represents only 57% of that of Argentina and 53% of that obtained by Chile.

The relevance of PISA-D for poorer education systems is because it offers a larger representation of poor and marginalised students (OECD 2018b) and it is constructed as a monitoring platform for SDG4 (OECD 2017; Ward 2018). In particular, PISA-D items provides widening coverage at the lower end achievement scales,[3] with the number of items representing level 2 or below being around 60% of the total PISA-D items pool. Furthermore, PISA-D relies on a contextual questionnaire which is more aligned to students conditions in low and middle income countries (OECD 2018b) gathering information on issues such as the prevalence of child labour among students, food security, degree of physical health, and education policies on repetition, multigrade settings, as well as information on inclusive learning environments (Penh 2018). PISA-D questionnaires are underpinned by the educational prosperity framework, a life-course approach to assessing children's outcomes and their salient drivers (Willms 2018). Importantly, the two salient features of PISA, i.e., a more granular definition of student performance at the bottom of the learning distribution and further details on social and economic contexts, allows us to measure whether there is a gap in school efficiency by school type as well as differences in equity between private and public schools.

3.1. DEA benchmark specification

For the DEA specification, we consider a set of inputs which are transformed into outputs mirroring an education production function (Hanushek and Woessmann 2011), with inputs/outputs being averaged at the school level. Our selection of inputs and outputs follows earlier studies on school efficiency; see, for instance, Agasisti and Zoido 2018; Cordero et al. 2017; De Jorge and Santín 2010), and also the detailed review on efficiency and education in De Witte and López-Torres (2017). Outputs are given by mean school values for math, reading and science scores and we use the first (out of ten) plausible value for each subject.[4] We include five educational inputs comprising different dimensions of school resources: three kinds of school infrastructure (physical, educational and IT), the student teacher ratio, and the school average of household wealth of students.[5]

Summary statistics for outputs and inputs[6] are shown in Table 1. Note that the working sample is derived by merging datasets from three questionnaires (students, teachers, and school/principal) and includes averaged variables for 705 schools, of which 207 are private schools (=29%) and 498 are public schools (=71%). The average scores for the whole LA sample is between 338-367 (Panel A, Table 1), around 73% of the OECD average for PISA 2018 (OECD 2019). Likewise, LA countries also have a lower stock of educational inputs; the student teacher ratio (STR) is around 24 (nearly twice as much as the OECD average), and around 32% of students are poor and severely poor.

[*Table 1 here*]

Descriptive statistics for inputs and outputs by school type are shown in Panels B and C of Table 1. Although there are no large differences on STR, other indices for school inputs are clearly larger for private schools and the extent of poverty is lower (showed by the family SES index) which ultimately yields a positive private school learning gap (with scores being between 11%-13% higher than in public schools). In other words, public schools in the LA region are disadvantaged in comparison to private schools, having a lower average performance coupled with a lower stock of inputs.[7]

3.2. Environmental variables - students, teachers and school

Once school efficiency scores are estimated, we employ an array of covariates to explain the degree of efficiency across public and private schools. These environmental variables can be thought of as a school's efficiency key determinants, albeit for poorer education systems with structural inequalities, which are organised into three categories: students, teachers and schools determinants (see Table 2). Firstly, among student determinants on efficiency, there is the gender composition in school (a socio-cultural learning driver in Latin America (Deutsch et al. 2013), preschool attendance, further barriers to achievement driven by language/indigeneity due to discrimination and language transition (Delprato 2019), as well as student engagement in different types of work (Post 2018) and student's overall health. Table 2 (Panel A, columns 3 and 5) shows that public schools are worse off in terms of their observed students characteristics compared to private schools. Public schools have a 7% lower average rate for preschool attendance, the likelihood of students working is larger by 2%-5% (paid work), and students attending public schools are also more likely to be from language minorities than private school students (18% versus 10%) and feel more insecure at school (lack of safety index).

[*Table 2 here*]

Secondly, teacher's characteristics included are: gender, qualifications, professional development, variables linked to payment and work environment satisfaction, and whether they teach across grades. Here, the main difference by school type is due to lower payment satisfaction and working conditions among public school teachers (Table 2 - Panel B, columns 3 and 5). Thirdly, we include three school features -i.e., school location, as rural schools operation costs tend to be higher,[8] financial stability (captured through the proportion of the funding coming from fees and government contributions), and school/class size (Panel C). In addition, a key school covariate for the analysis is school type. A school is defined as private if "...the school is managed directly or indirectly by a non-government organisation; e.g. a church, trade union, business, or other private institution."[9] As expected, public schools are logistically and economically disadvantaged. Private schools in rural areas are less common (18% against 43% of public rural schools in the sample); and public schools financial stability is considerably lower (over half of their budget is drawn from stable income while for private school this figure is 72%) and they are larger in size with their associated logistical challenges.

3.3. Policy variables and inequality indicators

To examine the leverage of policies on private and public schools efficiency, we also include variables for different strategies to compensate for students' lack of numeric and reading skills. These can vary from ability sorting and remedial classes, to monitoring reading and lowering learning goals (see Table B1) which can minimise the impact of repetition and dropout, a core issue haltering efficiency in resource constrained education systems. Table B1 (columns 3 and 5) highlights some variation on the applicability of these policies by school type. For instance, ability sorting and in-school remedial classes are more widespread in private schools than in public schools, and lowering goals for those students at risk is more prevalent among public schools. It should be noted that this variation is in line with broader differences in funding, admissions policies and accountability across these two education sectors (Elacqua et al. 2018).

Moreover, we rely on various inequality indicators (calculated for each school) to look into the efficiency-equity trade off (Table B2).[10] Indicators measure the degree of heterogeneity on the distribution of learning scores (i.e., Gini coefficient), the degree of inclusivity as in Agasisti and Zoido (2018) (i.e., proportion of students who obtain a score below level 2), and the association of family SES with achievement (correlation coefficient and proportion of disadvantaged students who are high performers). A comparison of school inequality by school type (Table B2, Panels B and C) shows that equality of opportunity differs by private and public schools -the association of family SES with achievement is larger in private schools, though the proportion of high achievers from deprived backgrounds is lower in public schools, whereas the distribution of education within the school population (Gini coefficient) is similar across the two school types.

4. Methodology

The nonparametric methodology Data Envelopment Analysis (DEA) (see, for instance: Thanassoulis 2001) is employed to compute efficiency scores for each school. The underlying assumption of DEA is that each school (or decision making unit) transforms inputs into outputs through a production process (Johnes 2004; Worthington 2001) yielding a measure of technical efficiency. This measure of technical efficiency is computed relative to the estimated frontier which represents the maximum output that each school can achieve given the available resources.

We rely on the concept of technical efficiency (Farrell 1957), that is, we assess whether units are reaching the highest possible level of product with the inputs used. This concept is presented in Figure 1 which shows a hypothetical situation where decision units (schools in our case) employ a single input to obtain one output (learning score). The most efficient decision units are those that manage to obtain more output with fewer inputs, and the union of the most efficient schools provides us with the enveloping frontier of best practice or most efficient schools; points below the frontier denote inefficient schools. For instance, in the case of decision unit B which is below the frontier (in other words, not achieving the maximum output level C given its level of input used A), it is not an efficient decision unit and its degree of inefficiency is measured as the ratio between the distances CB and CA.

[*Figure 1 here*]

Because we carry out a separate analysis for private schools and public schools, efficiency is measured with respect to the estimated frontier of each school type under different technologies. Let the superscript index $\xi \in$ (pri, pub) denotes school type. Each school k $(k = 1, ..., K)$ is defined by a combination of outputs $(m = 1, ..., M)$ and inputs $(n = 1, ..., N)$ under a given technology T, with a set of feasible input-output combinations:

$$T^{\xi} = \left\{(x, y) \in \mathbb{R}_{+}^{n+m} \text{ and } x \text{ can produce } y\right\} \tag{1}$$

where again ξ denotes each school type. The inefficiency measure is the degree by which output y_i has to be increased to move (y_i, x_i) onto the frontier and so it is a measure of inefficiency within the interval [1,∞). Because we invert scores, values of scores smaller than one indicate inefficiency and the estimated $\widehat{\theta}$ are bounded by (0,1]. Also, we tested for constant returns to scale (CRS) against variable return to scale (VRS) and we rejected the null hypothesis that the global technology is CRS.[11] The output-based measure of technical efficiency θ_i is calculated by solving the linear programming problem for each data point (schools: k = 1,..., K):

$$\begin{aligned} \widehat{F}_k^o(y_k, x_k, y, x|\text{VRS}) = \max_{\theta, z}\ &\theta \\ \text{s.t.} \sum_{k=1}^{K} z_k y_{km} &\geq y_{km}\theta_m, m = 1, ..., M \\ \sum_{k=1}^{K} z_k x_{kn} &\leq x_{kn}\theta_m, n = 1, ..., N \\ \text{and } z_k \geq 0, \sum_{k=1}^{K} z_k &= 1 \end{aligned} \tag{2}$$

where z_k are the process operating levels, and the additional restriction $\sum_{k=1}^{K} z_k$ =1 is added for Variable Returns to Scale (VRS). Estimated scores $\widehat{\theta}_k$ are obtained by solving Eq. (2) for private schools $(\widehat{\theta}_k^{\text{pri}})$ and for public schools $(\widehat{\theta}_k^{\text{pub}})$ separately. Efficiency scores are bias-corrected by bootstrapping to account for sample variation of the estimated frontier (Simar and Wilson 2000) using 1,000 repetitions for scores.[12]

The second step is to estimate the determinants of efficiency $\mathbf{z}_i$ (given in Table 2 and Tables B1-B2) by fitting the separate linear regression using as outcomes the estimated efficiency measures for private and public schools,

$$\widehat{\theta}_i^{\xi} = \mathbf{z}_i\beta + \varepsilon_i \tag{3}$$

where $\widehat{\theta}_i^{\xi} \in \left(\widehat{\theta}_k^{\text{pri}}, \widehat{\theta}_k^{\text{pub}}\right)$. A bootstrap version of the coefficients is needed here too because errors are not independent. We follow Simar and Wilson (2007) approach for the second-stage regression and use algorithm 2, where bias corrected DEA scores $\widehat{\theta}_i^{\text{bc}}$ are the dependent variables in Eq. (3), and we use 2,000 replications to obtain the marginal effects of environmental variables $\mathbf{z}$. Note that the inputs used for DEA are different from the variables used for the second stage regression. Inputs for the DEA formulation are: school resources, STR, and average school SES (see Table 1); and environmental or determinants of efficiency are students, teachers and schools characteristics (details on Table 2), with the latter group of school covariates not including indicators on infrastructure or average wealth.

5. Results

5.1. Efficiency scores for private and public schools and country estimates

DEA estimation of efficiency scores for the whole sample of private and public schools are shown in Table 3. Two versions of the technical efficiency estimates are shown in Panel A; that is, a standard version of technical efficiency (TE), and a bootstrap version of efficiency (TEBC) with their confidence intervals and bootstrap performance. Our focus is on TEBC estimates (Panel A, column 2). The mean efficiency score for the four LA countries is 0.82, hence there is room to increase efficiency by 18% across the whole education system. However, private schools ($\widehat{\theta}_k^{\text{pri}}$ = 0.88) are more technical efficient than public schools ($\widehat{\theta}_k^{\text{pub}}$ = 0.82). Thus, the scope to increase academic scores and efficiency while keeping the stock of inputs constant is larger in public schools (by 18%) (and in private schools by 12%). The gap between low and high efficiency schools, too, is wider among public schools where the efficiency level of bottom performing schools is 0.54; whilst for private schools efficiency for the less efficient schools is 0.69 (Panel B). The wider dispersion on efficiency in public schools is also clearly showed in Figure 2(a), and for private schools the density of $\widehat{\theta}_i$ is narrower and negatively skewed. Hence, estimates suggest that public schools as a whole (for four LA countries) are not making the most of available resources given their lower technical efficiency in comparison to private schools. Though it may be that school type's differential on parental education as a socially inherited characteristic (as shown by Gamboa and Waltenberg (2012) for the LA region) and other operating factors, might also explain this efficiency gap.

[*Table 3 here*]

Country estimates (Panel B, Table 3) indicate that there is an inverse relationship between the private-public efficiency gap and the overall efficiency of a country; that is, countries with more efficient education systems are also those where the sectors efficiency are more proximal and not far from each other. For instance, for the most efficiency country, i.e. Ecuador ($\widehat{\theta}_k = 0.86$), the differential on efficiency between private and public school is 6.4%, while for Paraguay (the less efficient country in the sample with a $\widehat{\theta}_k = 0.77$) the positive efficiency gap for private school is much larger (=12.2%). Guatemala and Honduras, on the other hand, sit in the middle in terms of overall efficiency and with lower efficiency gaps by school type (around 3.7%-4.1%, respectively). Figure 2(b) shows that within-country efficiency disparity across public schools is larger and there is less homogeneity between them (especially in Paraguay and Ecuador). These results clearly indicate that the efficiency scores are much more dispersed within countries than between them, suggesting that a comparison based on country averages would be misleading.

[*Figures 2(a) and 2(b) here*]

5.2. Factors associated with efficiency by school type

Table 4 displays the estimates of the second-stage regression (Eq. (3)) where we run three models for different samples; one for the whole sample with the private school dummy as a covariate, and the other two specifications are for both the private and the public school samples. Estimates for the whole sample (columns 1 and 3) further confirm the results of estimated efficiency scores of the previous section. In particular, the private school effects on efficiency is positive (=0.033, column 1) even after accounting for students background (indeed, students' SES is included among inputs) whereas, in addition, controlling for the full array of students, teachers and schools characteristics, the private school positive gap on efficiency still persists (with a statistically significant coefficient of 0.027, column 3). Aggregated results for the four countries indicate that LA private schools are more efficient than public ones; in fact, this efficiency gap holds beyond structural characteristics of schools. Whether this is a genuine private school effect, or either driven by unmeasured better environment (Gamboa and Waltenberg 2012) or peer group characteristics (Somers et al. 2004), is not fully conclusive.

[*Table 4 here*]

A follow-up empirical question is then to examine whether the private-public school efficiency gap can be attributed to specific factors placing private schools in a better position to operate and thus be able to produce more educational outputs with the same (or lower) levels of inputs. Estimates in Table 4 (columns 5 and 7) suggest that there are additional barriers which public schools are faced with, holding back their efficiency. Students' engagement in paid work or care work has a negative impact on public school efficiency (between 6.5%-8.5%), but they lack statistical significance in private schools. Similarly, the negative impact that the proportion of students who do not speak the language of the test at home (indigenous students) has on efficiency is nearly twice as large in public schools (-0.096) in comparison to private schools (-0.052). Preschool attendance, too, seems to widen private-public gap efficiency with a positive and relatively larger effect on private schools efficiency. Notably, the gender composition in private schools matters (i.e., schools with larger proportion of female students seems to be less efficient), but not in public schools. A teacher's lack of satisfaction with remuneration is an obstacle for efficiency in both types of schools (and so, too, is poor school climate), though it is a larger barrier among public schools, whilst teacher's qualifications and stability of school's income are only relevant positive drivers on efficiency in public schools. In general, estimates suggest that the private-public efficiency gap may be due to the diverging environmental characteristics of the pupil populations by school type (especially when combining work with study and ethnicity, after key inputs such as SES are accounted for).

5.3. Inequality and policies association with efficiency

Two questions are investigated here: (i) whether the differences in efficiency between private and public schools found above are related to inequality; (ii) the role of educational policies on efficiency. For the first question, estimates for inequality and inclusivity measures -net of students, teacher and schools characteristics as they are added as controls- are shown in Table 5. We find that more inclusivity and also more equality would benefit LA schools efficiency, regardless of the school type. Estimates for the two covariates (i.e., the Gini coefficient, and the proportion of low performers: achieving level 1 or below) and for the two school groups are negative, thereby schools efficiency can be increased by lowering within-school inequality or by improving baseline learning. However, the extent to which declining inequality is translated into increasing efficiency differs between private schools and public schools. In fact, there is a higher margin to raise efficiency by widening inclusivity and equality across public schools (i.e., the Gini estimated coefficient is -0.80/-0.77 for public schools and -0.58/-0.47 for private schools; and the negative coefficient associated to the proportion of low performers in school is nearly three times larger in public schools). What's more, in the case of inequality (math) and for public schools (Panel B, column 1), the positive and statistically significant coefficient (=0.074) for school prevalence of high achievers (level 2 or above) coming from deprived (low SES) family environments, again shows that efficiency can be enhanced by increasing inclusion in public schools, but in private schools, perhaps due to initial economic segregation on admissions, this covariate lacks statistical power.

[*Table 5 here*]

The benefits of shifting and reducing the populations of low performing students in schools can clearly be seen in Figure 3. For example, by significantly reducing a school's proportion of low performers from 0.80 to 0.10 in the public sector would increase efficiency by 0.25 (from -0.35 to -0.10), whereas in the private schools the change of efficiency will be smaller, around 0.10 (see Figure 3).

[*Figure 3 here*]

Figures 4(a)-4(b) and Figure 5 display the effect on efficiency for different values of school's policies coverage (marginal effects) addressing and targeting students falling behind in terms of math and readings skills. Figure 4(a) sub-plots outline the impact of three policies for students lacking math skills: extra support, remedial classes in schools and students grouped by ability. We find that the policy with the largest leverage/gradient for efficiency is providing remedial classes (especially in public schools); the other two policies, however, make little or no difference for either school type, with ability profiling policy having a flat gradient. Figure 4(b), furthermore, shows that additional homework does not appear to be helpful in enhancing either private schools or public schools efficiency, yet reallocation of students within a classroom, sitting weaker students with strong students, is quite valuable in the case of public schools (larger gradient).

[*Figures 4(a) and 4(b) here*]

Besides, in Figure 5, none of the three school policies aimed at those lacking reading skills (i.e., monitoring reading, outside remedial class, and lowering goals) are advantageous for efficiency; and, in practice, lowering goals seems to have a damaging effect on efficiency scores. In summary, from the range of policies outlined here, remedial math classes offered in schools and placing weaker students together with strong students are fruitful policies to increase efficiency in public schools; conversely, in the case private schools, the leverage effects of most policies are either small or null.

[*Figure 5 here*]

5.4. Country estimates of the private-public efficiency gap

In this section, for completeness, we provide country evidence on school type efficiency by running the DEA analysis (Eq. (2)) and the determinants of efficiency (Eq. (3)) for each country individually (Table 6). The focus is on assessing each country education system private-public efficiency gap (before and after full controls), rather than on the full range of students, teachers and school determinants of the efficiency frontier of each country.

[*Table 6 here*]

Estimates from Table 6 show that, out of the four countries included in the whole sample analysis, in only two of countries (Ecuador and Paraguay) there is a school type differential on efficiency. Results for the whole sample presented earlier on (in Table 4) are, as a result, driven by these two former countries. Private schools in Ecuador and Paraguay are more technically efficient than public schools by around 3.8%-4.7% (columns 2 and 8), even after considering differences on key drivers of achievement and learning, be it between the composition of students, teachers or among schools characteristics of private and public schools. As stated earlier, technical efficiency can be a narrow concept which does not take into account broader objectives that schools may have beyond efficiency, such as fostering soft skills and other society goals (e.g., equity) which are likely to differ between private schools and public schools.

6. Conclusions

Assessing the technical efficiency by school type -that is, how effectively private and public schools turn educational inputs into educational outputs- in a context of expansion of private enrollment in the Latin American (LA) region (Elacqua et al. 2018; Verger et al. 2018), is critical for the configuration of education systems. This is due to both the existing transfers of public funds towards the private sector (which in a scenario of education systems which are resources constrained is key) and the implications that a profit seeking or subsidised non-profit private sector has on the overall equality of a country education system. The unambiguous dual nature of LA education systems with their different challenges, calls for specific empirical answers of each sub-system efficiency equilibrium and its determinants. In addition, this exercise requires a comparable database fitted to the realities of less well-off education systems. Thus, in this paper, we used the recent PISA-D dataset (2017) which allowed us to examine the level and determinants of school efficiency at the secondary level by school type for the LA region based on four countries (i.e., Ecuador, Guatemala, Honduras and Paraguay). Specifically, we employed the Data Envelopment Analysis (DEA) technique to measure the efficiency of 705 schools, out of which 29% are private schools (=207) and the remaining 71% are public schools (or 498 schools), where outputs are the average scores for math, reading and science, and as inputs we used student inputs (household wealth) and school infrastructure inputs (physical, educational, IT and number of students per teacher).

We find that, after controlling by students and school infrastructure inputs in the DEA specification, for the whole LA region there is a 6% gap (or larger efficiency) on the level of outputs that private schools can obtain in comparison to public schools for a given level of inputs; the estimated efficiency score for private (public) schools is 0.88 (0.82). Put differently, there is larger scope in increasing efficiency by 18% in public schools in comparison to 12% in private schools. Of course, these results from the DEA efficiency analysis ignore the fact that public educational institutions have wider society goals beyond efficiency, such as having a leading role in fostering inclusion and improving other non-cognitive outputs/soft skills which are beyond our formulation (for instance, Cordero et al. (2017) use non-cognitive outcomes as determinants of efficiency). Furthermore, we found that the gap between the most efficient and the least efficient schools is greater among public schools. This, in turn, can be seen as an additional challenge for LA educational policy makers because they have to deal with a largely heterogonous education public sector. Though, at the same time, this can be used as an opportunity to identify best efficient practices within the public schools raising its mean efficiency. Moreover, when estimating efficiency for each country individually, we found that the most efficient countries are also those with the smallest difference between the most efficient and the least efficient schools. This highlights the usefulness of narrowing within-school efficiency heterogeneity and driven inequality to improve an overall country education system performance. In summary, when working with the aggregate sample, we found that private schools are more efficient than public schools in these four Latin American countries.

Regarding the determinants of efficiency, we found that public schools face different obstacles in terms of efficiency when compared to private schools. These obstacles, which are on top of household socio-economic background and school infrastructure, are diverse. Though the leading obstacles derives from students wider contexts which they bring into the education system. For public schools, the larger prevalence of students work in paid jobs and its negative impact on efficiency, as well as having a relatively larger proportion of students coming from minority languages or indigenous backgrounds who are also less likely to have attended preschool, are strong barriers for efficiency. This results in a school type efficiency gap where the public sector captures disadvantaged populations of students making their transitions into the secondary education systems, boosting access. In short, our estimates point towards a private-public efficiency gap which may be due to the diverging environmental characteristics of the pupil populations by school type. Behind this, one could argue that it may be the natural consequence of a dual or hybrid education system, that is segregation, where advantaged families choose higher performing schools (Bifulco and Ladd 2007; Gamboa and Waltenberg 2012) and the incentives to skim-off high achieving students through admission and other markers for selection.

As far as equity and efficiency are concerned, we found that the equity (as measured by the Gini coefficient or the degree of inclusivity) and efficiency trade-off is invalid and does not apply to the four LA countries as a whole. Then, it is feasible, regardless of the school type considered, to increase both equality in the system and its overall performance/efficiency. Indeed, we found that higher levels of inclusion and equality could benefit the efficiency of both types of education systems. Although there is greater scope for increasing efficiency by lowering inequality and boosting inclusion within public schools, where this empirical finding is obtained either through the comparison of the distribution of academic scores within school by the Gini coefficient or proportion of low achievers in a school. Regarding educational policies, too, we found another avenue to increase efficiency in public schools. The leading policy is to broaden the provision of remedial classes for those students at risk which would boost simultaneously inclusivity and school's efficiency. What's more, when analyzing the efficiency for each country individually, we found that only in Ecuador and Paraguay there are significant differences in efficiency levels between public and private schools, with these two countries driving the results obtained for the LA sample. This is negatively correlated with the importance of the private secondary education sector in each country, with efficiency gaps disappearing in the countries with largest participation of the private sector (Guatemala and Honduras).

Acknowledgements

We are grateful to the OECD for offering the PISA-D dataset online at: http://www.oecd.org/pisa/pisa-for-development/database/ on which this paper is based. Moreover, we would like to thank the two anonymous reviewers for their suggestions and comments which greatly improved the paper.

Disclosure statement

No potential conflict of interest was reported by the authors.

Notes

1. See, UNESCO Institute for Statistics database: http://data.uis.unesco.org/.

2. http://data.uis.unesco.org/

3. For example, while 77% of students on average across OECD countries in PISA (2018) had attained Level 2 proficiency in reading (the point at which students have acquired the technical skills to read) (OECD 2018a), only 36% do so for the four countries in our working sample.

4. An equivalent approach is employed in related studies such as Agasisti and Zoido (2018) and Cordero et al. (2017).

5. For a thorough discussion on school inputs selection within DEA analyses, see: De Witte and López-Torres (2017).

6. Note that the correlation, either among learning scores (the outputs) or among the chosen set of inputs, is common for studies employing DEA. For a discussion on this issue we direct the readers to López et al. (2016) who state the within-outputs or within-inputs correlations are not a concern as long as there is a high degree of correlation among the two elements of DEA: outputs with inputs. This holds in our analysis with ρ being high, varying between 0.45 and 0.73. We thank an anonymous referee for raising this issue.

7. Similar results are obtained when comparing private and public school from urban areas based on the TERCE learning survey (Treviño et al. 2016).

8. An exemplary cost exercise on different modes of delivery of education in rural areas in Latin America, see: UNICEF (2017).

9. This is question 6 from the principal questionnaire. The public school in question 6 is defined by the following option: "This is a school managed directly or indirectly by a public education authority, government agency, or governing board appointed by government or elected by public franchise."

10. For a discussion of the equality and equity within the framework of educational prosperity used in PISA-D, see Willms (2018).

11. Results from these tests are available from authors upon request.

12. After testing, we find that the homogeneous bootstrap is appropriate rather than the heterogenous bootstrap.

References

Agasisti, T., Ricca, L., 2016. Comparing the efficiency of italian public and private universities (2007–2011): an empirical analysis. Italian Economic Journal 2 (1), 57–89.

Agasisti, T., Zoido, P., 2018. Comparing the efficiency of schools through international benchmarking: Results from an empirical analysis of oecd pisa 2012 data. Educational Researcher 47 (6), 352–362.

Alexander, W. R. J., Haug, A. A., Jaforullah, M., 2010. A two-stage double-bootstrap data envelopment analysis of efficiency differences of new zealand secondary schools. Journal of Productivity Analysis 34 (2), 99–110.

Antequera, G. O., 2019. Eficiencia técnica y eficacia como indicadores de desempeño de instituciones educativas. Ph.D. thesis, Universidad Nacional de Córdoba.

Badunenko, O., Mozharovskyi, P., 2016. Nonparametric frontier analysis using stata. The Stata Journal 16 (3), 550–589.

Badunenko, O., Tauchmann, H., 2019. Simar and wilson two-stage efficiency analysis for stata. The Stata Journal 19 (4), 950–988.

Bifulco, R., Ladd, H. F., 2007. School choice, racial segregation, and test-score gaps: Evidence from north carolina's charter school program. Journal of Policy Analysis and Management 26 (1), 31–56.

Cherchye, L., De Witte, K., Ooghe, E., Nicaise, I., 2010. Efficiency and equity in private and public education: A nonparametric comparison. European Journal of Operational Research 202 (2), 563–573.

Cordero, J. M., Santín, D., Simancas, R., 2017. Assessing european primary school performance through a conditional nonparametric model. Journal of the Operational Research Society 68 (4), 364–376.

Cordero Ferrera, J. M., Crespo-Cebada, E., Santín González, D., et al., 2010. Factors affecting educational attainment: evidence from spanish pisa 2006 results. Regional and Sectoral Economic Studies 10 (3), 55–76.

De Jorge, J., Santín, D., 2010. Determinantes de la eficiencia educativa en la unión europea. Hacienda pública española 193, 131–155.

de Oliveira, P. R., Belluzzo, W., Pazello, E. T., 2013. The public–private test score gap in brazil. Economics of Education Review 35, 120–133.

De Witte, K. D., López-Torres, L., 2017. Efficiency in education: a review of literature and a way forward. Journal of the Operational Research Society 68 (4), 339–363.

Delprato, M., 2019. Parental education expectations and achievement for indigenous students in latin america: Evidence from terce learning survey. International Journal of Educational Development 65, 10–25.

Delprato, M., Chudgar, A., 2018. Factors associated with private-public school performance: Analysis of talis-pisa link data. International Journal of Educational Development 61, 155–172.

Deutsch, J., Dumas, A., Silber, J., 2013. Estimating an educational production function for five countries of latin america on the basis of the pisa data. Economics of Education Review 36, 245–262.

Elacqua, G., Iribarren, M., Santos, H., 2018. Private schooling in latin america: Trends and public policies. Education Division Social Sector: Inter-American Development Bank, out.

Elacqua, G., Martinez, M., Santos, H., Urbina, D., 2016. Short-run effects of accountability pressures on teacher policies and practices in the voucher system in santiago, chile. School Effectiveness and School Improvement 27 (3), 385–405.

Farrell, M. J., 1957. The measurement of productive efficiency. Journal of the Royal Statistical Society: Series A (General) 120 (3), 253–281.

Gamboa, L. F., Waltenberg, F. D., 2012. Inequality of opportunity for educational achievement in latin america: Evidence from pisa 2006–2009. Economics of Education Review 31 (5), 694–708.

Hanushek, E. A., Woessmann, L., 2011. The economics of international differences in educational achievement. In: Handbook of the Economics of Education. Vol. 3. Elsevier, pp. 89–200.

Iregui-Bohórquez, A. M., Melo-Becerra, L. A., Ramos-Forero, J. E., Iregui-Bohórquez, A. M., Melo-Becerra, L. A., 2006. Evaluación y análisis de eficiencia de la educación en colombia. Borradores de Economía; No. 381.

Johnes, G., Virmani, S., 2020. The efficiency of private and public schools in urban and rural areas: moving beyond the development goals. International Transactions in Operational Research 27 (4), 1869–1885.

Johnes, J., 2004. Efficiency Measurement. Edward Elgar Publishing.

López, F. J., Ho, J. C., Ruiz-Torres, A. J., 2016. A computational analysis of the impact of correlation and data translation on dea efficiency scores. Journal of Industrial and Production Engineering 33 (3), 192–204.

Mancebón, M. J., Calero, J., Choi, Á., Ximénez-de Embún, D. P., 2012. The efficiency of public and publicly subsidized high schools in spain: Evidence from pisa-2006. Journal of the Operational Research Society 63 (11), 1516–1533.

Mizala, A., Romaguera, P., Farren, D., 2002. The technical efficiency of schools in chile. Applied Economics 34 (12), 1533–1552.

OECD, 2017. Pisa for development and the sustainable development goals, pisa for development brief 17.

OECD, 2018a. Pisa 2018 insight and interpretations.

OECD, 2018b. Pisa for development. technical report.

OECD, 2019. Pisa 2018 results (volume i): What students know and can do.

Östh, J., Andersson, E., Malmberg, B., 2013. School choice and increasing performance difference: A counterfactual approach. Urban studies 50 (2), 407–425.

Penh, P., 2018. Education in cambodia: Findings from cambodia's experience in pisa for development.

Post, D., 2018. Incidencia del trabajo infantil en el logro académico de alumnos de sexto grado: Hallazgos del terce. Education Policy Analysis Archives 26.

Simar, L., Wilson, P. W., 2000. A general methodology for bootstrapping in non-parametric frontier models. Journal of applied statistics 27 (6), 779–802.

Simar, L., Wilson, P. W., 2007. Estimation and inference in two-stage, semi-parametric models of production processes. Journal of econometrics 136 (1), 31–64.

Somers, M.-A., McEwan, P. J., Willms, J. D., 2004. How effective are private schools in latin america? Comparative education review 48 (1), 48–69.

Spaull, N., 2013. Poverty & privilege: Primary school inequality in south africa. International Journal of Educational Development 33 (5), 436–447.

Sutherland, D., Price, R., Gonand, E., 2009. Improving public spending efficiency in primary and secondary education. OECD Journal: Economic Studies (1), 1–30.

Thanassoulis, E., 2001. Introduction to the theory and application of data envelopment analysis. Springer.

Treviño, E., Villalobos, C., Baeza, A., 2016. Handbook on measuring equity in education.

UNICEF, 2017. Estudio de costos comparados de la educación rural en salta. secundarias rurales mediadas por tic.

Vandenberghe, V., Robin, S., 2004. Evaluating the effectiveness of private education across countries: a comparison of methods. Labour economics 11 (4), 487–506.

Vera, M. L., Gertel, H., Giuliodori, R., 2008. Productividad educativa en las escuelas argentinas: Una aplicación de fronteras estocásticas. Investigaciones de Economía de la Educación, 71.

Vera, M. L., et al., 2011. La importancia del sistema público de educación para el desarrollo de una economía: Análisis para las distintas jurisdicciones de la argentina durante la década de los 90. Ph.D. thesis, Universidad Internacional de Andalucía.

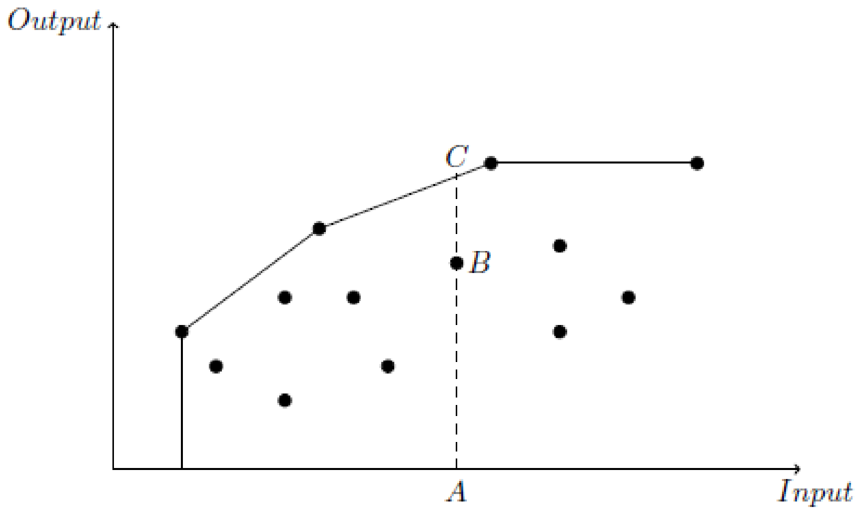
Verger, A., Moschetti, M., Fontdevila, C., Saltman, K., Means, A., 09 2018. The expansion of private schooling in latin america, 131–155.

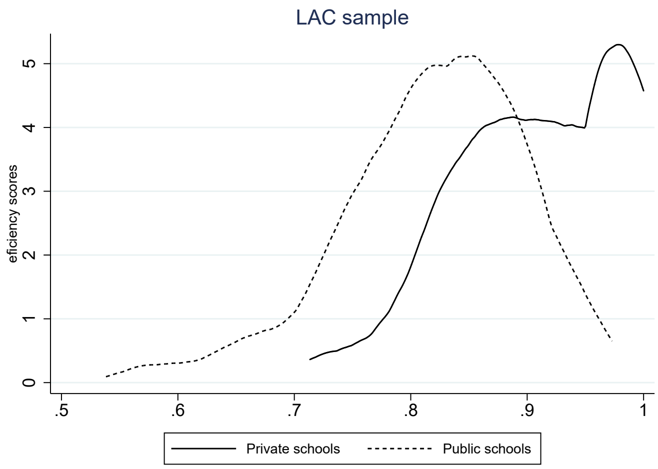
Ward, M., 2018. Pisa for development: Results in focus.

Willms, J. D., 2018. Educational prosperity.

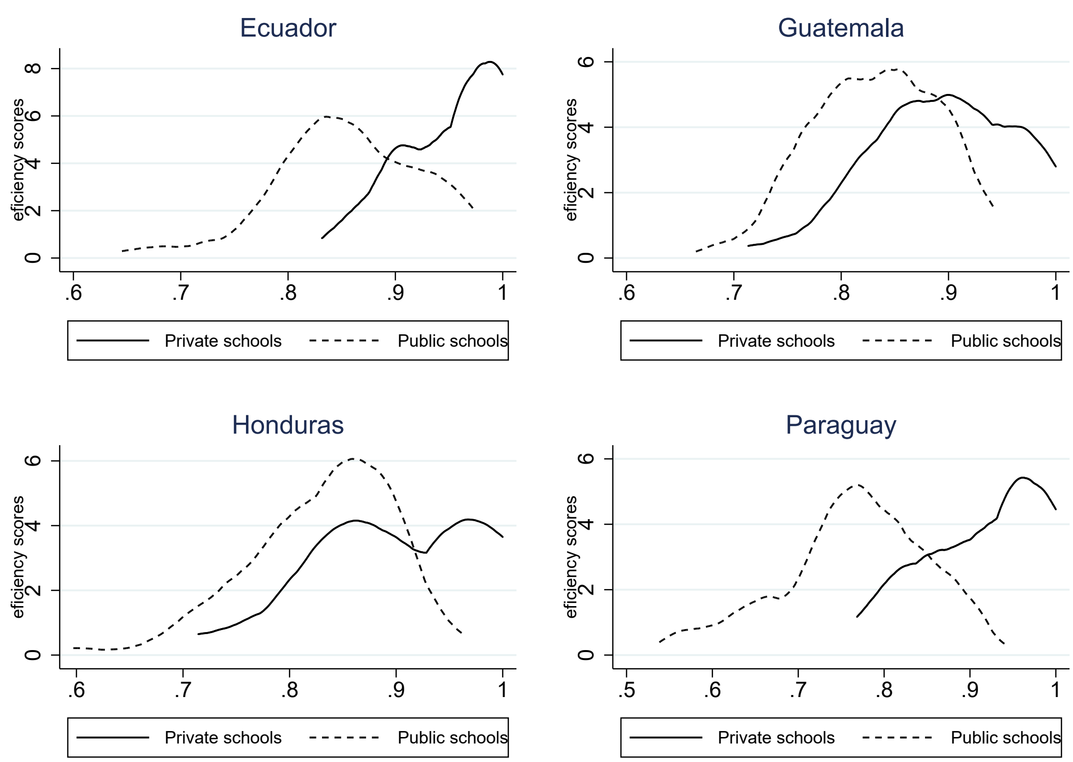
Worthington, A. C., 2001. An empirical survey of frontier efficiency measurement techniques in education. Education economics 9 (3), 245–268.

Figure 1: Technical efficiency - DEA





((a)) Whole sample



((b)) Countries

Figure 2: Efficiency scores

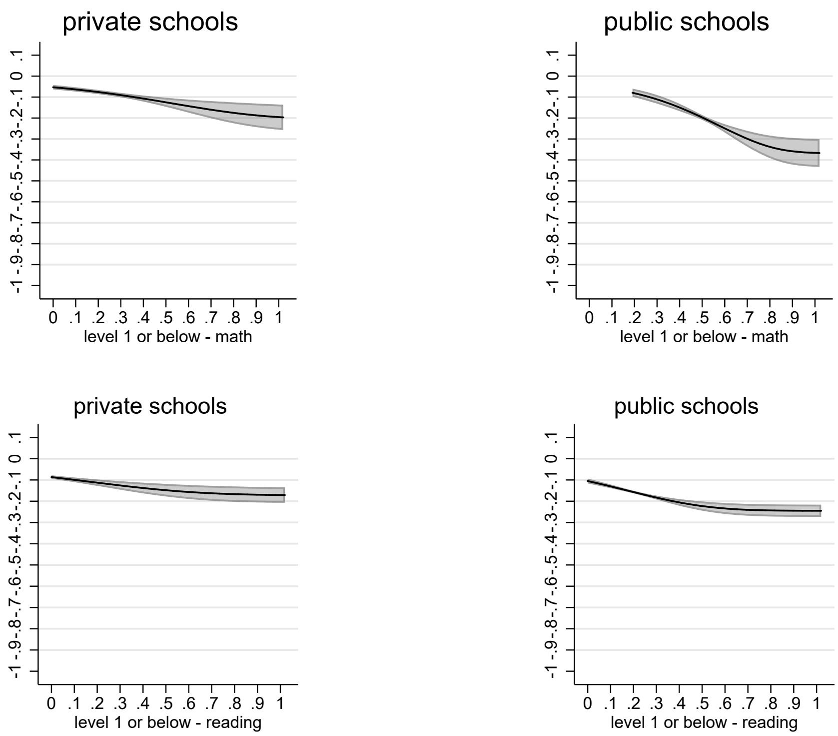
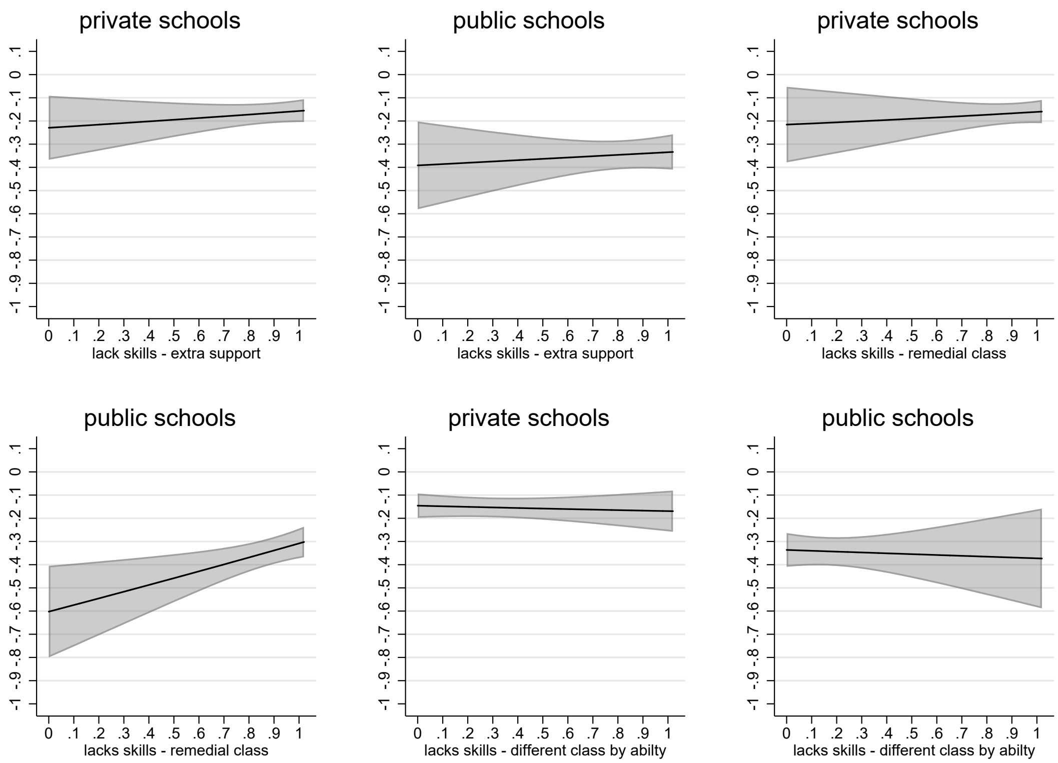
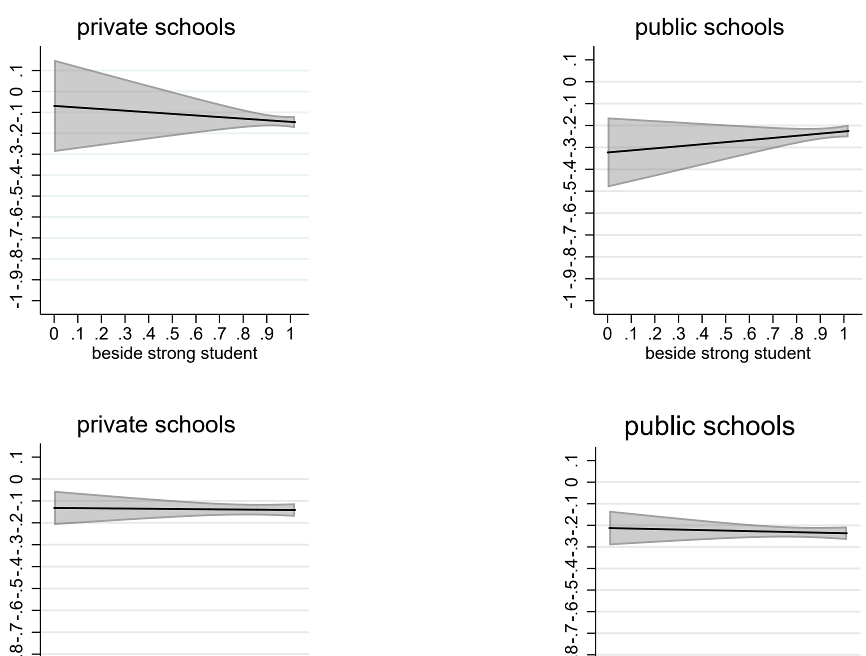


Figure 3: Marginal effects of degree of inclusivity on efficiency

Notes: (1) Shaded area are 95% CI for marginal effects. (2) Model includes the specific covariates, plus country dummies.



((a)) School policy for lack of math skills



((b)) School policy for lack of reading skills

Figure 4: Marginal effects on efficiency scores

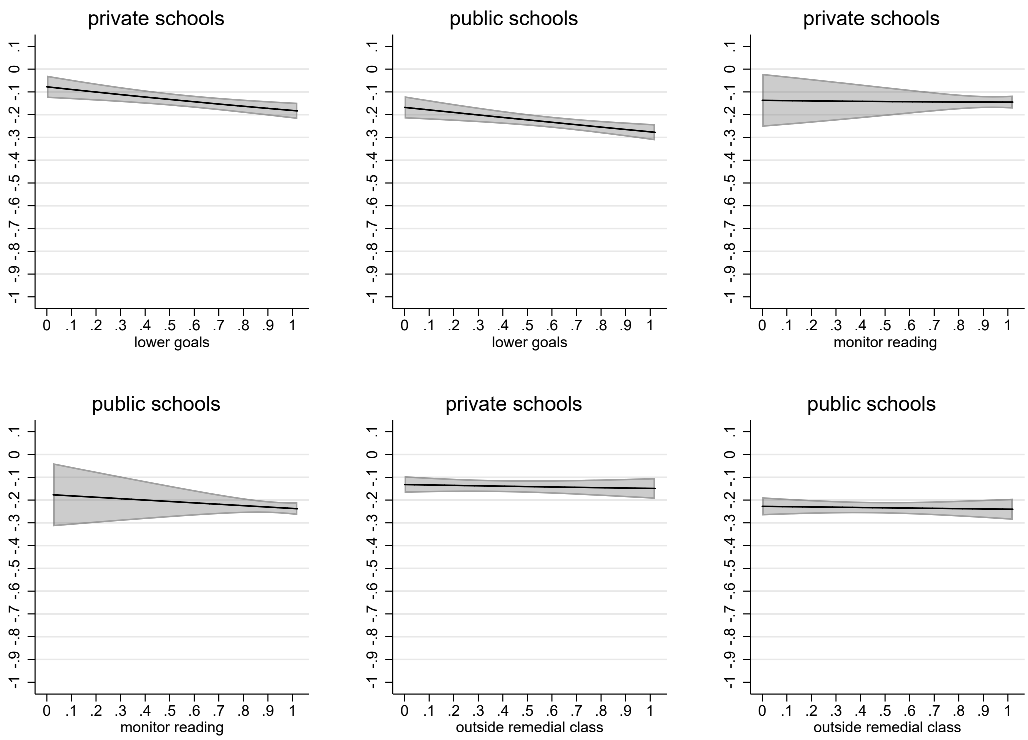


Figure 5: Marginal effects on efficiency scores for policies to address lack of reading skills

Notes: (1) Shaded area are 95% CI for marginal effects. (2) Model includes the specific covariates, plus country dummies.

Table 1: DEA specification - outputs, inputs. Descriptive statistics

	Mean	SD	Min	Max
	(1)	(2)	(3)	(4)
Panel A - LAC sample (N = 705)				
Outputs				
Math	337.86	50.93	164.51	503.47
Reading	371.24	54.55	230.75	523.58
Science	366.53	45.60	244.25	514.59
Inputs				
Family SES	-1.33	0.79	-3.69	1.30
School infrastructure - physical	0.29	0.81	-3.95	1.55
School infrastructure - educational	-0.13	0.90	-2.10	2.35
School infrastructure - IT	0.10	0.97	-1.54	2.15
Student teacher ratio (inverse)	0.07	0.08	0.00	1.00
Panel B - Private school sample (N = 207)				
Outputs				
Math	367.70	50.23	237.91	503.47
Reading	406.83	53.14	287.65	523.58
Science	394.67	45.81	274.43	514.59
Inputs				
Family SES	-0.74	0.89	-3.15	1.30
School infrastructure - physical	1.01	0.59	-2.80	1.55
School infrastructure - educational	0.64	0.95	-2.10	2.35
School infrastructure - IT	0.98	0.86	-1.54	2.15
Student teacher ratio (inverse)	0.07	0.07	0.01	0.66
Panel C - Public school sample (N = 498)				
Outputs				
Math	325.46	45.86	164.51	471.49
Reading	356.45	47.93	230.75	506.94
Science	354.83	40.10	244.25	481.82
Inputs				
Family SES	-1.58	0.59	-3.69	0.59
School infrastructure - physical	0.00	0.69	-3.95	1.47
School infrastructure - educational	-0.45	0.66	-1.97	1.84
School infrastructure - IT	-0.27	0.75	-1.54	2.03
Student teacher ratio (inverse)	0.06	0.08	0.00	1.00

Notes: (1) Whole sample is composed of aggregated results for the four PISA-D countries: Ecuador, Guatemala, Honduras and Paraguay. (2) For details on the original variables used for the DEA specification, see Table A1. (3) Note that inputs are scaled up to positive values for the DEA analysis.

Table 2: DEA - second stage variables. Descriptive statistics

	LAC sample		Private school sample		Public school sample	
	Mean	SD	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - Students						
Gender-female	0.50	0.17	0.52	0.20	0.49	0.16
Preschool - attended	0.83	0.15	0.88	0.15	0.81	0.14
Repeat - lower secondary	0.09	0.12	0.09	0.13	0.09	0.12
Home language - not the test language	0.15	0.28	0.08	0.19	0.18	0.31
Work - paid	0.14	0.12	0.11	0.10	0.16	0.13
Work - unpaid	0.14	0.14	0.12	0.14	0.14	0.13
Work - care	0.26	0.17	0.24	0.19	0.27	0.16
Skipped whole day	1.54	0.27	1.59	0.30	1.52	0.25
Health - lack of	0.11	0.10	0.09	0.09	0.12	0.10
School travel - long	1.83	0.52	1.91	0.57	1.79	0.49
Safety index - lack of	0.75	0.48	0.64	0.44	0.79	0.49
Classroom climate index	-0.02	0.43	-0.04	0.42	-0.01	0.43
Panel B - Teacher						
Gender-female	0.59	0.36	0.54	0.38	0.62	0.35
Multigrade teaching	0.10	0.25	0.11	0.26	0.10	0.24
Degree	0.81	0.31	0.75	0.35	0.84	0.28
Professional development	0.36	0.37	0.34	0.37	0.37	0.37
Satisfied - wage	0.36	0.39	0.49	0.41	0.30	0.37
Satisfied - benefits	0.41	0.40	0.55	0.40	0.35	0.38
Satisfied - working conditions	0.30	0.35	0.37	0.37	0.27	0.33
Panel C - School						
Rural	0.35	0.48	0.18	0.39	0.43	0.49
Funding stable	0.60	0.44	0.72	0.41	0.54	0.43
Enrolment	675.57	819.70	494.83	568.62	750.69	893.57
Class size	30.13	12.98	29.69	13.08	30.32	12.94

Notes: (1) For details on the original variables used for constructing the second stage variables, see Table A1.

Table 3: Estimated efficiency scores

	TE	TEBC	TEBC lower bound	TEBC upper bound	Bootstrap performance	N
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - Whole Sample Estimates						
LAC sample	0.860	0.824	0.854	0.791	22.805	705
Private schools	0.912	0.881	0.909	0.843	12.599	207
Public schools	0.860	0.819	0.854	0.781	21.279	498
BC scores	Mean	SD	IQR	Min	Max	N
Panel B - Country Estimates						
Whole sample	0.824	0.078	0.103	0.540	0.974	705
Ecuador	0.861	0.068	0.097	0.641	0.974	161
Guatemala	0.827	0.061	0.095	0.654	0.949	176
Honduras	0.832	0.069	0.087	0.598	0.970	194
Paraguay	0.776	0.088	0.108	0.540	0.957	174
Private schools	0.881	0.065	0.104	0.690	0.980	207
Ecuador	0.920	0.043	0.064	0.808	0.978	33
Guatemala	0.869	0.063	0.090	0.690	0.978	76
Honduras	0.871	0.072	0.112	0.690	0.980	58
Paraguay	0.886	0.062	0.106	0.748	0.971	40
LAC sample	0.881	0.065	0.104	0.690	0.980	207
Public schools	0.819	0.079	0.104	0.538	0.973	498
Ecuador	0.855	0.068	0.091	0.645	0.973	128
Guatemala	0.832	0.058	0.093	0.665	0.942	100
Honduras	0.830	0.068	0.092	0.597	0.962	136
Paraguay	0.765	0.085	0.091	0.538	0.944	134
LAC sample	0.819	0.079	0.104	0.538	0.973	498

Notes: (1) Technical efficiency (TE) scores are radial measure of technical efficiency, and they are derived using variable returns to scale (VRS) and homogenous bootstrap (for bias corrected version). Results from these two tests are available from the authors upon request. (2) TE: technical efficiency scores, output orientated (inverted); TEBC: technical efficiency scores bias corrected using 2,000 bootstrap repetitions. (3) Lower and upper bootstrap confidence interval at 95% level. (4) Bootstrap performance is given by three times the ratio of bias squared to variance for radial measures of technical efficiency; the statistic is large so it indicates the appropriateness of bias correction (smoothed homogenous bootstrap). (5) Estimation commands used are: `teradial` and `teradialbc` (see: Badunenko and Mozharovskyi 2016).

Table 4: Second stage estimates - whole sample and private and public schools samples

	LAC sample				Private schools		Public schools	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
private school	0.0328***	(0.0058)	0.0271***	(0.0056)				
student gender-female			-0.0069	(0.0132)	-0.0428**	(0.0182)	-0.0119	(0.0174)
preschool - attended			0.0414***	(0.0153)	0.0610**	(0.0270)	0.0455**	(0.0186)
repeated - lower secondary			-0.0932***	(0.0181)	-0.1620***	(0.0272)	-0.0279	(0.0231)
home language - not the test language			-0.0801***	(0.0109)	-0.0526**	(0.0222)	-0.0968***	(0.0128)
work - paid			-0.0400*	(0.0213)	0.0450	(0.0369)	-0.0649***	(0.0247)
work - unpaid			-0.0648***	(0.0195)	-0.1484***	(0.0277)	-0.0055	(0.0239)
work - care			-0.0656***	(0.0143)	0.0135	(0.0198)	-0.0855***	(0.0186)
skipped whole day			-0.0263***	(0.0095)	-0.0389***	(0.0129)	-0.0015	(0.0124)
health - lack of			-0.0279	(0.0230)	0.0153	(0.0379)	-0.0162	(0.0271)
school travel - long			0.0061	(0.0045)	-0.0024	(0.0060)	0.0080	(0.0060)
safety			-0.0292***	(0.0057)	-0.0375***	(0.0097)	-0.0311***	(0.0066)
classroom climate index			-0.0086	(0.0068)	-0.0068	(0.0108)	-0.0076	(0.0083)
student gender-female			0.0046	(0.0061)	0.0058	(0.0093)	-0.0002	(0.0077)
multigrade teaching			-0.0024	(0.0092)	0.0093	(0.0138)	-0.0066	(0.0116)
degree			0.0311***	(0.0077)	0.0051	(0.0101)	0.0292***	(0.0109)
professional development			-0.0009	(0.0061)	-0.0013	(0.0090)	-0.0023	(0.0073)
satisfied - wage			-0.0177***	(0.0066)	-0.0194**	(0.0098)	-0.0251***	(0.0087)
satisfied - benefits			0.0021	(0.0069)	0.0096	(0.0102)	-0.0024	(0.0083)
satisfied - working conditions			-0.0064	(0.0066)	-0.0109	(0.0094)	-0.0043	(0.0079)
school - rural			-0.0001	(0.0058)	-0.0116	(0.0099)	0.0006	(0.0066)
funding stable			0.0114**	(0.0052)	0.0005	(0.0084)	0.0122**	(0.0062)
enrolment			0.0000***	(0.0000)	0.0001***	(0.0000)	0.0000***	(0.0000)
class size			0.0007***	(0.0002)	0.0009***	(0.0003)	0.0006**	(0.0002)
Observations	705		705		207		498	

Notes: (1) Estimates are based on Simar and Wilson (2007) two-stage efficiency analysis (algorithm 2), with 2,000 bootstrap replications for estimating confidence intervals and standard errors for the regression coefficients; and 1,000 bootstrap replications for the bias correction of DEA scores. (2) Bootstrapped standard errors (SE) in parentheses. (3) Estimation command used: `simarwilson` (Badunenko and Tauchmann 2019).
Significance levels: * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table 5: Second stage estimates for inequality indicators

	Math inequality		Reading inequality	
	Coeff	SE	Coeff	SE
	(1)	(2)	(3)	(4)
Panel A - private schools				
Gini	-0.5812***	(0.1685)	-0.4673***	(0.1489)
Level 1 or below	-0.1236***	(0.0174)	-0.1105***	(0.0144)
Level 2 or above - low SES	-0.0092	(0.0143)	0.0035	(0.0113)
Correlation - SES	-0.0074	(0.0100)	-0.0016	(0.0098)
N	207		207	
Panel B - public schools				
Gini	-0.8000***	(0.1085)	-0.7693***	(0.0919)
Level 1 or below	-0.3212***	(0.0347)	-0.2705***	(0.0224)
Level 2 or above - low SES	0.0738**	(0.0335)	-0.0280	(0.0201)
Correlation - SES	0.0066	(0.0063)	-0.0060	(0.0057)
N	498		498	

Notes: (1) Second stage estimates based on Simar and Wilson (2007) (algorithm 2). (2) Estimates includes student, teacher and school controls from Table 4. (3) Education inequality indicators are calculated for each school and based on math and reading scores: Gini (coefficient); Level 1 or below (% of student in the school whose performance is at level 1 or below, math score ≤ 420, reading score ≤ 407); Level 2 or above - low SES (% of student in the school whose performance is at least level 2 and who are poor - wealth index in the bottom half of the distribution); correlation SES (ρ school coefficient between students' scores and family SES). (4) Bootstrapped standard errors (SE) in parentheses.
Significance levels: * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table 6: Private-public school gap, second stage country estimates

	Ecuador		Guatemala		Honduras		Paraguay	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Private dummy	0.0447***	0.0476***	-0.0070	-0.0083	0.0068	0.0167	0.0571***	0.0382***
	(0.0102)	(0.0103)	(0.0077)	(0.0080)	(0.0105)	(0.0102)	(0.0100)	(0.0114)
Full controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	161	161	176	176	194	194	174	174

Notes: (1) For details on the estimation procedure and full controls, see Table 4.
Significance levels: * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$.

Table A1: Second stage variable description. Names of PISA-D variables

Type	Description	Original variables
i) DEA specification		
Cognitive outcomes	math, reading and science scores	y_pv1math, y_pv1read, y_pv1scie
Non-cognitive outcomes	socialisation index	st068q01ta to st068q06ta
	positive attitudes index	st067q03ta to st067q08ta
	positive feelings index	st017q01na to st017q11na
Inputs	family SES	escs15
	school infrastructure - physical	sc011q01na to sc011q08na and sc012q01na to sc012q15na
	school infrastructure - educational	tc017q01na to tc017q20na
	school infrastructure - IT	tc035q01na to tc035q18na
	student teacher ratio (inverse)	sc003q01ta, sc003q02ta and sc004q01na, sc004q02na
ii) Second stage variables		
s_gender	student female	st004d01t
s_preschoold	attended preschool	st005q01ta
s_repeat_lowsec	repeated at lower secondary	st009q02ta
s_work	student works	st020q01na to st020q06na
s_langn_test_no	does not speak language of test at home	st021q01ta
s_skip_wholeday	in the last two weeks, skipped a whole school day	st078q01ta
s_health_all_no	student health, lack of	st018q01na
s_travel_school	time from home to school	st061q01na
s_safe_index	safety at school, index, lack of	st069q01na to st069q03na
s_schexptch_index	school expectations, teacher's help	st072q01na to st072q11na
s_classclimate_index	classroom climate, index	st074q01ta to st074q05ta
t_gender	teacher gender, female	tc001q01t
t_multigrade	multigrade teaching	tc005q01na
t_edu_degree	degree	tc003q01na
t_train_profdev	professional development, last 12 months	tc014q02ta
t_satis_wage	satisfied with wage	tc034q01na
t_satis_benef	satisfied with benefits	tc034q03na
t_satis_workccond	satisfied with working conditions	tc034q04na
sc_rural	school, rural	ruralstr
sc_type_private	school, private	sc006q01ta
sc_funding_stable	school funding stable, % coming from govt and fees	sc008q01ta and sc008q02ta
sc_enrolment	school total enrolment	sc003q01ta and sc003q02ta
sc_class_size	class size	clsize
t_lackstud_sortabi	sort by ability	tc027q03na
t_lackstud_remedial	remedial class	tc027q05na
t_lackstud_extrasupp	extra support	tc027q06na
t_strat_lowgoals	lower goals	tc029q03na
t_strat_monitorread	monitoring reading	tc029q07na
t_strat_outsideremedial	outside remedial class	tc029q09na
t_strat_extrahomework	extra homework	tc029q10na
t_strat_besidestrongstud	sit beside strong student	tc029q12na

Table B1: Summary statistics - second stage variables. Policy indicators

	Whole sample		Private schools sample		Public schools sample	
	Mean	SD	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)
Students lack reading or numeric skills - policies						
Sort by ability	0.21	0.31	0.27	0.35	0.18	0.29
Remedial class	0.78	0.34	0.85	0.29	0.76	0.35
Extra support	0.81	0.30	0.83	0.30	0.80	0.30
Strategies for those lacking reading skills						
Lower goals	0.62	0.40	0.59	0.41	0.63	0.40
Monitor reading	0.92	0.21	0.91	0.23	0.93	0.20
Outside remedial class	0.44	0.40	0.42	0.41	0.44	0.39
Extra homework	0.81	0.29	0.81	0.31	0.82	0.29
Beside strong student	0.94	0.16	0.95	0.15	0.94	0.16
N	705		207		498	

Table B2: Summary statistics - second stage variables. Inequality school indicators

	Math			Reading		
	Mean	Min	Max	Mean	Min	Max
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - whole sample (N=705)						
Gini	0.08	0.00	0.18	0.08	0.00	0.19
Level 1 or below	0.88	0.00	1.00	0.70	0.00	1.00
Level 2 or above - low SES	0.08	0.00	1.00	0.25	0.00	1.00
Correlation - SES	0.07	-1.00	1.00	0.08	-1.00	1.00
Panel B - private school sample (N=207)						
Gini	0.07	0.00	0.14	0.07	0.00	0.15
Level 1 or below	0.77	0.00	1.00	0.51	0.00	1.00
Level 2 or above - low SES	0.12	0.00	1.00	0.35	0.00	1.00
Correlation - SES	0.10	-1.00	1.00	0.13	-1.00	1.00
Panel C - public school sample (N=498)						
Gini	0.08	0.00	0.18	0.08	0.00	0.19
Level 1 or below	0.92	0.20	1.00	0.78	0.00	1.00
Level 2 or above - low SES	0.06	0.00	1.00	0.20	0.00	1.00
Correlation - SES	0.06	-1.00	1.00	0.06	-1.00	1.00

Notes: (1) Education inequality indicators are calculated for each school. (2) Indicators based on math and reading scores: Gini (coefficient); Level 1 or below (% of student in the school whose performance is at level 1 or below, math score $\leq$ 420, reading score $\leq$ 407); Level 2 or above - low SES (% of student in the school whose performance is at least level 2 and who are poor - wealth index in the bottom half of the distribution); correlation SES (ρ school coefficient between students' scores and family SES).