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The “true” private school effect using PISA 2012-Mathematics: evidence from 40 countries

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Abstract: It is known that in most countries, students of private schools outperform students in public schools in international assessments. However, the empirical literature recognises that assessing the true effect of private school attendance requires addressing selection and sorting issues on both observables and unobservables. The existing empirical evidence on the private school effect mostly covers OECD and Latin American countries, with little evidence on other parts of the world. There is recent emerging country specific evidence doubting the existence of a private school advantage. I use PISA 2012 data for Mathematics and two different methodologies to derive bias-corrected estimates of the “true” private-dependent and independent school effect for 40 countries. A robust private school advantage if found only in a handful of countries. Public schools perform equally well as private subsidised schools and outperform independent schools. Accounting for both peer effects and selection is necessary when evaluating school effectiveness, especially in the case of independent schools..

JEL Classification Codes: C52, I24, L33
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1. Introduction

Parents decide whether to enrol their children to a private instead of a public school by assessing the benefits and costs associated with this decision. Perceived benefits relate to more autonomy and flexibility in deciding curricula, more resources, better peer groups and safer school environment, among others. Private schools tend to attract not only students from more privileged backgrounds, but also better performing students (OECD, 2011). Differences in socioeconomic backgrounds between private and public schools can be very large (examples are several countries in Latin America, such as Uruguay, Brazil and Peru as well as Middle Eastern countries).

There is definite evidence that, based on a simple comparison without accounting for student background, private school students perform better in the overwhelming majority of countries and the raw PISA score difference ranges from only a few points to more than 100 points; in a minority of countries public schools outperform private schools (for example Taiwan and Thailand). After accounting for student socioeconomic background and other observables, the evidence is mixed. In fact PISA finds that when public schools attract a similar student population to that of private schools and given similar levels of autonomy, the private school advantage is no longer evident (PISA in focus, 2011).

Assessing the true effect of private school attendance hinges on addressing both the effect of observable covariates (associated with student and family background characteristics and school demographics) and selection effects. There is sorting of students into private and public schools; for example, students from better socioeconomic backgrounds enrolling in private schools. This results in endogeneities, as more privileged/higher ability private school students achieve better results, which in turn leads to an overestimation of the private school effect (French and Kingdon, 2010; Mcloughlin, 2013).

It is known that when estimating the true effect of private school attendance the estimation model is likely vulnerable to omitted variable bias, as parental background is expected to be correlated with various unobserved student and school characteristics. One would then need a suitable measure or proxy for ability, which may prove elusive; such problems magnify if the objective is to estimate such effects across countries rather than for a single country, since then consistency and comparability issues are important.

I use the PISA 2012 mathematics assessment for 15-year old students to evaluate the effect of attending private schools on test scores; student performance in mathematics is a better proxy for school effectiveness compared to reading and science. I first derive base estimates using multilevel modelling (mixed effect regression with random intercepts); subsequently I evaluate the effect of additional selection due to omitted variable bias.

Section 2 provides a non-exhaustive summary of the literature. Section 3 describes the methodology and data used, while section 4 presents and discusses the findings.

2. Literature review

A review of the literature on the effectiveness of private schools reveals a general agreement that in OECD and partner countries, most of the difference in PISA scores in favour of private school students can be attributed to the ability of private schools to attract students from better socioeconomic backgrounds, better performing students and private schools possessing better material resources. There is no evidence that the private school sector contributes to raising the performance of the school system as a whole (PISA in focus, 2011). However, studies using controlled regressions often find a private school advantage, or at least advantages associated with sub-types of private schools.

Donkers and Robert (2003; 2008) used earlier data (PISA 2000) to compare the effectiveness of private-dependent, private-independent and public schools for 15-year olds in 19 OECD countries, after controlling in a step-wise manner for sociological, demographic, behavioural and attitudinal characteristics of parents and students, as well as teaching and learning conditions and school climate. They used multi-level analysis, but they did not explicitly account for unobserved confounding factors. They find that private government-dependent schools seem to be more effective than comparable public schools and attribute this to better school climate in private schools; however, private-independent schools were found to be less effective than comparable public schools.

The challenges of uncovering the true effect of private education across countries using different available econometric techniques are also evident in the literature. Vandenberghe and Robin (2004) attempted to estimate the effect of private vs. public education on pupils' achievement, using the 2000 OECD PISA survey, taking into account the potential bias due to the existence of unobserved confounding factors. They used three methods: IV regression, Heckman's 2-stage approach and Propensity Score Matching and compared the estimates. Overall, they find that private education does not generate systematic benefits. However, they found significant differences in results between parametric and non-parametric estimators. Using different methods is expected to result in different estimates, as each method has its own weakness. For example, OLS, IV and Heckman-correction methods impose linearity in the outcome equation. The authors also find that the main obstacle in deriving reliable estimates using the IV and Heckman approaches is the difficulty in finding valid instruments. This problem is overcome when using Propensity Score Matching; however, this method is undermined (especially when using cross-section data) by its inability of dealing with unobserved selection.

The literature on developing countries also stresses the presence of heterogeneity in findings and the difficulties associated with ascertaining whether any private school advantage found can be fully ascribed to private schools. This is because not all empirical studies deal convincingly with unobserved/unmeasurable differences in the socio-economic backgrounds of private and public school pupils; hence, the private school advantage is likely to be over-estimated. Day-Ashley et al. (2014) reviewed 21 studies (mostly of medium quality and only three high quality) on six developing countries, the majority of them for India. They find only moderate evidence supporting the assumption that private school pupils achieve better learning outcomes than pupils in the public school system.

Similarly, Mcloughlin (2013), after reviewing the literature in developing countries concludes that, while evidence broadly supports the view that students attending private schools are achieving better results even after accounting for social background, the extent of the true private sector advantage, when found, is often marginal. Ultimately, claims of a "private sector effect" can be made only after rigorously using both covariates to separate the effect of schools from that of student and parental background and accounting for selection effects, i.e., the endogenous advantage arising from sorting of children from better-off, better informed families into private schools.

Evidence on Latin American countries can be found in Somers, McEwan and Willms (2004) and McEwan (2000). Somers, McEwan and Willms (2004) questioned the common supposition that private schools are relatively more effective than public schools at improving student outcomes ("private school effect") in Latin American countries using UNESCO data for 10 countries and a multilevel approach. They find that private-public differences in achievement are only partly accounted for by better socioeconomic status of private schools and much more by differing peer-group characteristics between the two types of schools. After accounting for peer group characteristics, they find that the average private school effect is near zero, with some variance around the mean. Furthermore, they consider this an upper bound effect, since selection may be biasing the estimates in favour of private schools. McEwan (2000) compared the academic outcomes of seventh- and eighth-graders in public and private schools (Catholic subsidized, non-religious subsidized and private non-subsidized) in Argentina and Chile (both countries have a long history of public support for private schools). In both countries, Catholic subsidized schools were found to be more effective than public schools in producing student outcomes, although it is suggested that these effects are probably an upper bound to the true effects, due to selection bias.

Studies which employ empirical strategies which use selection on observables to assess the bias arising from selection on unobservables to account for selection bias (as is this study) are increasingly coming to light. This emerging evidence points to private schools performing no better than public schools (or even worse). Cardak and Vecci (2013) estimated the effect of Catholic school attendance on high school completion and university commencement in Australia after accounting for selection on unobservables using the assumption of equality between selection on observables and unobservables. They find that this effect is smaller than previously estimated and negative treatment effects cannot be ruled out. Elder and Jepsen (2014) find that Catholic schools do not appreciably boost test scores and that findings point to sizeable negative effects of Catholic schooling on mathematics achievement. Earlier, Altonji, Elder and Taber (2005) estimated the effect of attending a Catholic high school on a variety of outcomes in the US. They conclude that Catholic high schools substantially increase the probability of graduating from high school and possibly attending college; however, they find little evidence of an effect on test scores.

Recent emerging large scale evidence from the US, also casts doubt on existing beliefs that private schools perform better. The book: *The Public School Advantage* by Lubienski and Lubienski (2013) is one of the most comprehensive studies of private vs. public school performance in mathematics, utilizing data on test scores from more than 300,000 students and more than 15,000 schools. They find that after controlling for student characteristics, student socioeconomic background along with school demographic factors, the private school advantage disappears and often becomes negative.

Finally, Ryan (2013) used PISA data for 2000 and 2009 for Australia, observing that mathematics scores declined by 19 points; he found that the decline in scores was concentrated among private schools, while based on changes in student characteristics during the period, test scores should not have declined.

In this paper I use a methodologically consistent framework to derive bias-adjusted estimates after accounting for selection on unobservables in 40 countries (from Europe, North America, Oceania, Middle East, South America and East Asia), in which the size of the private sector is non-trivial. The evidence generalizes certain country-specific findings mentioned in this section and suggests that a robust private school advantage is not frequently observed.

3. Data and Methodology

3.1 Data

PISA 2012[1], which follows on the steps of previous PISA surveys (2000/2002, 2003, 2006 and 2009/2010), intends to measure what 15-year old students in grade 7 or higher (that is students approaching the end of their compulsory schooling) can do with what they learn at school. It emphasizes the mastery of processes, the understanding of concepts, and the ability to function in various types of situations. Over the years country participation in PISA has increased and the 2012 survey was conducted in 34 OECD countries and 31 partner countries/economies. The 2012 survey focused mainly on mathematics with more than half a million students competing in the participating countries, representing a population of 28 million 15-year olds (OECD, 2014).

The PISA 2012 surveys contain information and simple indices on student, family background, school and teacher characteristics, as well as information on occupational status and educational level of parents, immigration and language background, measures of engagement with and at school (such as skipping classes, index of sense of belonging and index of attitude towards learning activities and outcomes), student drive and motivation (such as index of perseverance, index to openness in problem solving and index of intrinsic and instrumental motivation in mathematics), mathematics self-beliefs (such as index of mathematics self-efficacy, index of

[1] The development of PISA 2012-Mathematics was coordinated by an international consortium of educational research institutions contracted by the OECD, under the guidance of a group of mathematics experts from participating countries.

mathematics self-concept and index of mathematics anxiety) and various indices of disposition towards mathematics, disciplinary climate at school and teacher-student relations.

School level variables and indices contain information on school and class size, student-teacher ratio, school type, availability of computers, quality of teaching staff, ability grouping, use of assessments and school responsibility for curriculum and assessment. School level scale indices contain information on teacher shortages, quality of school resources and infrastructure, teacher and student behaviour and teacher morale.

The survey also contains the constructed index of Economic, Social and Cultural Status (ESCS), which is derived from three other indices: (a) highest occupational status of parent, (b) highest educational level of parents in years of education and (c) home possessions. The index of home possessions incorporates all items of the indices on household wealth (whether students lived in a household which had certain possessions, such as a room of their own for the student, internet connection, number of cellular phones, number of TVs, etc.); household cultural possessions (such as books on literature, poetry, etc.); household educational resources (such as a desk, computer, etc.); and books at home. The ESCS index was derived using principal component analysis of standardized variables (OECD mean of zero and standard deviation of one)[2], taking the factor scores of the first principal component as the measure of the ESCS index.

Schools are classified as either public or private, according to whether the ultimate decision maker is a private entity or a public one. This is combined with information on the percentage of total funding which comes from government sources. The generated index of school type allows for the identification of three categories: (1) government-independent private schools controlled by a non-government organization or with a governing board not selected by a government agency, that receive less than 50% of their core funding from government agencies,

[2] Negative values for an index do not necessarily imply that students responded negatively to the underlying questions; a negative value merely indicates that the respondents answered less positively than all respondents did on average across OECD countries. Likewise, a positive value on an index indicates that the respondents answered more favourably, or more positively, on average, across OECD countries.

(2) government-dependent private schools controlled by a non-government organization or with a governing board not selected by a government agency that receive more than 50% of their core funding from government agencies and (3) public schools controlled and managed by a public education authority or agency.

The proportion of missing values for important variables such as school type and index of social cultural and economic status is small (generally under 3%). Missing values were imputed using the method of relating observations in the original data to a set of fundamental variables with no or few missing values.

Table 1A in the Appendix contains information on size of public school sector, proportion of government-dependent vs. private-independent private schools and proportion of schools with a positive peer group index by school type (index of Economic, Social and Cultural Status at the school level) for the 40 countries in this study in which private schools account for at least 3%, but not exceeding 90% of all schools[3]. Over all countries, private schools account for nearly a quarter of all schools[4], but there is heterogeneity both between and within groups of countries. In European countries private schools are predominantly government-dependent (exceptions are Greece and Switzerland); the opposite is the case in other areas of the world, especially in the Middle East where almost all private schools are independent. Across all countries, about half of all private schools are government-dependent.

As expected, private schools, especially independent schools have better peer groups compared to public schools. Across all countries, about two-thirds of private-dependent schools and three-quarters of independent schools have a positive peer group index, compared to only one-third of public schools. Differences are particularly severe in Latin American countries, where only 2% of public schools have a positive peer group index, compared to 42% and 62% for

[3] Countries with a very small public school sector and hence excluded, are Macao and Hong Kong.
[4] This is higher than the 18% of private schools in PISA 2012, because countries with only a small proportion of private schools are excluded from the study.

private-dependent and independent schools, respectively. The opposite is the case in East Asian countries, in which peer groups in independent and public schools are much more similar.

3.2 Methodology

Isolating causal effects is difficult in most contexts and particularly so when assessing private school effectiveness. The often cited private school advantage may be due to unobserved student, family and other characteristics being correlated with private school attendance; such characteristics are expected to influence student performance, while at the same time influencing decisions on which school type students will be enrolled in.

In the first stage of the investigation I use multilevel analysis – the methodology of choice in assessing school affect differences and handling the nested structure of PISA data. Subsequently, I use multiple regression analysis and the same model specification, as a starting point to investigate the effect of remaining selection on unobservables; the approach is based on the idea that the amount of selection on the observed explanatory variables in a model provides a guide to the amount of selection on the unobservables. This framework allows the bounding of the estimated private school effect between two values: the base coefficient estimates (such as the fixed coefficients from the mixed effects estimation) and the bias-corrected estimates, after accounting for remaining selection (assuming that selection on unobservables is proportional to selection on observables).

3.2.1 A multilevel model of attainment with school effects

Student achievement scores are associated to a variety of student, family, school and environmental characteristics. One can distinguish school level variation from various school level (observed) characteristics - such as sector, school resources location, etc., from residual (unobserved) variation between schools. The second, can be seen as being associated to differences in school quality (Hanushek & Rivkin, 2010).

The model which takes into account the hierarchical structure of the data and the estimation of random intercepts associated with a student *i* belonging to school *j* is:

$$SCORE_{ij} = X_{ij}\beta + S_j\gamma + u_j + \varepsilon_{ij}$$

where X_{ij} are the individual characteristics of student i in school j identified in the literature as close determinants of school performance and Sj are the characteristics (resources) of school j shared by all students attending school *j*. The random component u_j is an estimate of the systematic effect of school j on scores, over and above the effect of the observed school related covariates (S*j*) and ε_{ij} is a student level residual. The school type variables (private-dependent, independent and pubic) which are part of the vector X, are the focus of interest.

When students are clustered in groups, such as schools, randomly selected students in the same school are expected to be more similar compared to students in another school; consequently, we expect test scores to be more similar than scores in a different school, since they share features of the particular school such as teacher characteristics and student demographics. One needs, therefore, to take into account clustering; otherwise the standard errors of regression coefficients will be underestimated (especially of predictors measured at the group level such as whether the school is private vs. public, single sex vs. mixed sex, etc.). One reason for using multilevel modelling with random effects is to obtain correct standard errors[5]; an additional reason is to estimate and assess the remaining (residual) between school variation after accounting for observed school level variation.

3.2.2 Assessing additional selection

Given the inherent difficulties in isolating effects of variables such as school type in complex environments (schools, family background, etc.), multilevel modelling cannot entirely account for problems associated with selection on unobservables and omitted variable bias. The approach followed in this study starts with the estimation of a multiple regression model which controls for

[5] Other methodologies using survey data with multistage design can also address the problem of clustering.

available observables (student, family and school characteristics and peer group quality) with standard errors clustered at the school level. The estimated coefficients are expected to be of similar magnitude to the fixed coefficients from the estimated multilevel model. Subsequently, I estimate the extent of the potential bias associated with unobserved selection.

Following Altonji et at. (2005), Oster (2013; 2015) built on their (and related) intuitive methodologies and connected the theory to empirical work. The additional insight is to recognize that coefficient stability is not informative on its own, but it needs to be combined with information on R-squared movements; in the presence of multiple controls, using additional information (and a general estimator) is important, as it is possible to observe stable coefficients and large R-squared movements even when large biases exist. This methodology allows for more flexibility in examining the robustness of estimated effects under selection, the estimation of selection bias and bias-adjusted effects.

In the simple case of a treatment X and a single observable, consider the linear equation:

$$Y = \beta X + \gamma_1 w_1^0 + W_2 + \in \qquad (1)$$

where X is the treatment of interest with coefficient β, index $W_1 = \gamma_1 w_1^0$ is the observed control with coefficient γ_1, W_2 is a vector (linear combination) of unobserved controls multiplied by their true coefficients and the error $\in$ is orthogonal to X, W_1 and W_2. Under equal selection (selection on unobservables as important as selection on observables), consider the regression of Y on X with a sample coefficient $\beta°$ and R-squared $R°$, and the regression of Y on X and w_1^0 with coefficient $\tilde{\beta}$ and R-squared: $\tilde{R}$. Furthermore, define R_{max} as the R-squared that would have been obtained had we been able to regress Y on X, w_1^0 and W_2. Then, using standard omitted variable bias formulas, it can be shown that the bias, Π:

$$\Pi = [\beta° - \tilde{\beta}] \frac{\mathrm{Rmax} - \tilde{R}}{\tilde{R} - R°}, \qquad (2)$$

and the bias-corrected estimate of β is:

$$\beta^* = \tilde{\beta} - [\beta^\circ - \tilde{\beta}]\,\frac{\text{Rmax}-\tilde{R}}{\tilde{R}-R^\circ} \qquad (3)$$

Given that $\Pi = \tilde{\beta} - \beta^*$, it follows that: $\frac{\tilde{\beta}-\beta^*}{\beta^\circ-\tilde{\beta}} = \frac{\text{Rmax}-\tilde{R}}{\tilde{R}-R^\circ}$. So, under the equal selection assumption, the ratio of the change in coefficients is equal to the ratio of the change in R-squared.

Oster (2013; 2015) derived a general estimator under proportional selection (selection on unobservables is proportional to selection on observables) with a coefficient of proportionality δ and multiple observables. Under proportional selection, this estimator can produce multiple solutions for β, but the solution is unique under equal selection (δ = 1), under the added assumption that the bias from unobservables is not so large that it biases the direction of the covariance between the observables and the treatment variable.

As discussed in Altonjie et al. (2002) and Oster (2015), the value δ = 1 is a suitable bounding value. In applications, one can either calculate the value of δ so that β = 0 (degree of selection necessary to explain away the estimate), or calculate the bias-adjusted β while assuming that δ = 1. However, the approach is application specific. In our case, the objective is to select reasonable bounding assumptions on R_{max} and δ to generate bounds for the treatment effect. The particulars of the application along with intuition can help in selecting an R_{max} between $\tilde{R}$ and 1, and δ values which are bounded below at 0 and above at some arbitrary δ.

4. Results and discussion

4.1 Raw score differences

Tables 1a and 1b report results separately for the private-dependent vs. public (Table 1a) and the private-independent vs. public school (Table 1b) comparisons. A country enters into the table when the size of the private school subsector is not trivial (at least three schools and 100 students in the subsector). In total, 32 countries are reviewed in Table 1a and 31 in Table 1b (40 countries in total).

Countries with very small private-independent school subsector (and small number of schools and students in the PISA data) which were excluded from the analysis are: Czech Republic (2 schools), Germany (2 schools), the Netherlands (2 schools) and Slovakia (1 school); Belgium (with 3 schools and 100 students), was marginally included. Countries with small private-dependent school subsector excluded from the analysis are: Greece (2 schools), the USA (less than 40 students in the sample), Jordan (1 school) and Qatar (1 school). Schools with less than 10 students participating in the survey were excluded from the analysis; given that the PISA data have a considerable number of schools with few participating students, this can affect the reliability of estimates on the effectiveness of private schools.

The mean raw score difference between both types of private schools and public schools (reported in column 1 of both tables) is, with very few exceptions, heavily in favour of private schools, especially in Latin American and the Middle East; however, in East Asia the opposite is the case, especially for private-dependent schools. Across all countries, the mean differential is much larger when private-independent schools are compared to public schools (about 0.66 of a standard deviation), compared to the corresponding differential when private-independent schools are compared to public schools (0.29 of a standard deviation). The mean gaps are much larger in Latin America and Middle East. In East Asia the gap is in favour of public schools when compared to private-dependent schools, while the evidence is mixed for private-independent schools when compared to public schools.

4.2 Estimation of private school effects

The dependent variable is the standardized mathematics score, to facilitate comparison between countries. As in many other studies using PISA data I use the average of the five mathematics plausible values in the data[6,7].

[6] In the PISA test, individual students only answer a minority of questions, i.e., we do not observe the true score, rather a set of observed test scores. Given values of the model parameters, a score can be imputed to individuals. Given model uncertainty, this is done multiple times generating multiple ‘plausible values’. Since the statistical

The list of controls includes the following student and family characteristics: Age, gender, preschool attendance, being first generation immigrant, being second generation immigrant, community size, family structure, Social, Cultural and Economic Status index (with components: highest occupational status of parents; highest educational level of parents in years of education according to ISCED; and home possessions[8]), out of school study time, parental and student attitudes (index of parental pressure and index of perseverance). It also includes the following school and institutional characteristics: Private school sub-type (private-dependent or independent), number of schools in the community, attending same sex schools (all-boy, all-girl school), class size, school size, proportion of certified teachers, dummies for ability grouping at school, school autonomy and teacher shortages, as well as indices on student climate and school educational resources. Finally the model also controls for peer group quality at the school level (derived from the Social, Cultural and Economic Status index), while estimates are also derived excluding peer group quality controls, to evaluate their contribution to the private school effect.

The sample size varies by country and for the majority of countries is around 5,000 observations. Larger samples are available for the UK, Finland, Belgium, Switzerland, Colombia, UAE, Qatar and Jordan, ranging from 7,000 to 12,000 observations, while for Italy, Spain, Canada, Mexico and Brazil they are even larger ranging from 14,000 to more than 33,000 observations.

Column 2 in Table 1a presents the fixed coefficients of private-dependent school attendance (vs, public school attendance) from mixed effects regressions. In three-quarters of the countries private-dependent schools perform equally well as public schools. I four countries

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model used to generate the plausible values is likely inadequate, the uncertainty in the national scores is likely underestimated.

[7] For comparison I also used the specialized Stata program *pv* (authored by Kevin Macdonald), for application in the education assessment literature, which estimates statistics when there are multiple plausible values. There were no substantial differences in estimates that would affect the conclusions on the nature of the private-public school differentials. Furthermore, derivation of bias-adjusted estimates requires a first-stage OLS based estimation of controlled estimates.

[8] The index of Home Possessions comprises all items on the indices of wealth, cultural possessions (books on poetry and works of art at home) and home educational resources, as well as books in the home recoded into a four-level categorical variable.

(Belgium, Canada, Argentina and Brazil) a significant private school effect is found. In seven countries (Czech Republic, Germany, UAE, Costa-Rica, Mexico, Taiwan and Thailand) the opposite is the case. On average, over all OECD countries, the effect of attending private-dependent schools is indistinguishable to that of attending public schools. On the other hand, in Latin American and East Asian countries a moderate in magnitude effect in favour of public schools is found.

Table A3 in the Appendix presents the random intercept variance estimates and variance partition coefficients (residual between-school variation as a proportion of total variation in scores) after controlling for school and student effects. This is an estimate of what is left in between school variation after controlling for important student and school predictors. Remaining between school variance differs substantially by country. It low (but still statistically significant) for several (mostly OECD) countries (such as Denmark, Finland, Ireland, Sweden, New Zealand) and outside OECD in Taiwan. However, there are many countries for which remaining between school variance is a large proportion of total variance (examples are the Netherlands, Italy, France, Germany, Brazil, Mexico, Indonesia, Thailand and Vietnam). This suggests that in the case of large remaining between school variance, estimated coefficients are potentially biased due to unobserved school characteristics (omitted variable bias).

Column 2 of Table 1b presents the fixed coefficients of private-independent school attendance (vs, public school attendance) from mixed effects regressions. In the majority of countries independent schools and public schools perfume equally well. An independent school advantage is, however, found in several countries: Belgium (which has a very small independent school sector), Greece, Canada, Ireland, New Zealand, Qatar, Brazil and Indonesia). In six countries (Switzerland, Australia, Costa Rica, Japan, Taiwan and Thailand) a public school advantage if found.

Table 1a: Estimated effects on the standardized Mathematics PISA score – Private-dependent vs. Public schools

Country	(1) Raw score diff: Private - Public	(2) Mixed effects regression Fixed coefficients	(3) Multiple regression: coefficients	(4) Bias-adjusted effect	
OECD				δ = 0.5	δ = 1
Austria*	0.517 (0.054)	-0.040 (0.179)	-0.111 (0.154)	-0.262	-0.380
Belgium	0.547 (0.024)	0.212 (0.065)	0.233 (0.052)	0.154	0.074
Czech Republic	-0.025 (0.068)	-0.262 (0.110)	-0.244 (0.101)	-0.184	-0.227
Denmark	0.270 (0.037)	-0.022 (0.071)	0.026 (0.070)	-0.031	-0.106
Finland	0.237 (0.064)	0.070 (0.075)	0.066 (0.073)	0.023	0.007
France*	0.341 (0.037)	-0.121 (0.120)	-0.079 (0.096)	-0.178	-0.283
Germany	0.367 (0.060)	-0.460 (0.174)	-0.279 (0.143)	-0.450	-0.637
Hungary	0.174 (0.044)	-0.102 (0.112)	-0.090 (0.108)	-0.118	-0.187
Ireland	0.275 (0.048)	0.073 (0.055)	0.067 (0.048)	0.067	0.068
Italy	-0.409 (0.052)	-0.091 (0.127)	-0.133 (0.129)	-0.088	-0.042
Netherlands	-0.047 (0.033)	0.059 (0.143)	0.126 (0.097)	0.184	0.242
Poland	0.566 (0.092)	0.022 (0.176)	0.184 (0.181)	0.097	0.003
Portugal	0.381 (0.051)	-0.018 (0.134)	-0.198 (0.109)	-0.347	-0.516
Slovakia	0.427 (0.058)	0.044 (0.141)	0.047 (0.118)	-0.081	-0.208
Spain	0.406 (0.022)	0.051 (0.056)	0.036 (0.053)	-0.042	-0.126
Sweden	0.169 (0.043)	0.122 (0.073)	0.082 (0.065)	0.061	0.039
Switzerland	0.390 (0.102)	0.350 (0.342)	0.024 (0.312)	-0.104	-0.247
United Kingdom	0.128 (0.033)	0.027 (0.071)	0.025 (0.063)	-0.021	-0.068
Canada	0.664 (0.037)	0.360 (0.098)	0.345 (0.092)	0.291	0.236
Australia	0.731 (0.026)	0.046 (0.092)	-0.051 (0.077)	-0.260	-0.512
Mean	***0.305***	***0.016***	***0.004***	***-0.064***	***-0.144***
MENA					
UAE	0.694 (0.033)	-0.192 (0.088)	-0.125 (0.085)	-0.219	-0.320
South America					
Argentina	0.800 (0.030)	0.267 (0.102)	0.333 (0.086)	0.206	0.065
Brazil	1.04 (0.061)	0.328 (0.164)	0.305 (0.140)	0.085	-0.176
Chile	0.396 (0.025)	0.014 (0.135)	-0.016 (0.089)	0.055	0.129
Colombia	0.148 (0.057)	-0.217 (0.148)	-0.124 (0.134)	-0.177	-0.231
Costa Rica	0.875 (0.061)	-1.06 (0.272)	-0.583 (0.299)	-0.890	-1.25
Mexico	0.431 (0.055)	-0.381 (0.144)	-0.279 (0.142)	-0.431	-0.605
Peru	0.744 (0.067)	-0.031 (0.150)	0.145 (0.135)	0.032	-0.090
Mean	***0.633***	***-0.154***	***-0.031***	***-0.160***	***-0.308***
East Asia					
Indonesia	-0.524 (0.032)	0.179 (0.190)	0.013 (0.182)	0.175	0.361
Korea	-0.067 (0.031)	0.091 (0.102)	-0.007 (0.073)	0.050	0.110
Taiwan	-0.997 (0.046)	-0.519 (0.156)	-0.601 (0.097)	-0.542	-0.480
Thailand	-0.413 (0.033)	-0.430 (0.140)	-0.342 (0.073)	-0.295	-0.247
Mean	***-0.500***	***-0.170***	***-0.234***	***-0.153***	***-0.064***
Overall mean	***0.289***	***-0.051***	***-0.038***	***-0.101***	***-0.175***

Note: Clustered standard errors in parentheses in column 3.

* For Austria and France there is no information to separate private from dependent and independent.

Table 1b: Estimated effects on the standardized Mathematics PISA score – Private-Independent vs. Public schools

Country	**(1) Raw score diff: Private - Public**	**(2) Mixed effects regression: Fixed coefficients**	**(3) Multiple regression: Coefficients**	**(4) Bias-adjusted effect:**	
OECD				**δ = 0.5**	**δ = 1**
Belgium	1.63 (0.057)	0.615 (0.100)	0.597 (0.086)	0.440	0.270
Denmark	0.415 (0.078)	0.057 (0.126)	0.117 (0.099)	0.048	-0.018
Greece	1.29 (0.077)	0.516 (0.167)	0.812 (0.123)	0.699	0.576
Ireland	0.882 (0.085)	0.287 (0.105)	0.223 (0.108)	0.095	-0.049
Italy	0.334 (0.059)	0.000 (0.154)	-0.130 (0.129)	-0.206	-0.287
Poland	0.742 (0.089)	-0.019 (0.252)	0.060 (0.185)	-0.119	-0.326
Portugal	1.10 (0.055)	-0.051 (0.149)	-0.040 (0.110)	-0.348	-0.712
Spain	0.607 (0.033)	0.070 (0.085)	0.036 (0.079)	-0.046	-0.133
Switzerland	-0.300 (0.058)	-0.543 (0.137)	-0.763 (0.150)	-0.869	-0.938
United Kingdom	0.956 (0.051)	0.238 (0.152)	0.266 (0.133)	0.116	-0.056
Canada	0.656 (0.052)	0.268 (0.105)	0.249 (0.120)	0.127	-0.012
USA	0.030 (0.050)	-0.162 (0.118)	-0.506 (0.109)	-0.632	-0.764
Australia	0.240 (0.020)	-0.113 (0.051)	-0.128 (0.051)	-0.206	-0.290
New Zealand	0.923 (0.065)	0.301 (0.114)	0.241 (0.097)	0.075	-0.114
Mean	**0.679**	**0.105**	**0.073**	***-0.059***	***-0.204***
MENA					
Jordan	0.904 (0.046)	0.238 (0.136)	0.475 (0.114)	0.343	0.193
Qatar	1.09 (0.018)	0.256 (0.098)	0.312 (0.100)	-0.079	-0.601
UAE	0.750 (0.023)	-0.156 (0.089)	-0.164 (0.075)	-0.373	-0.619
Mean	***0.915***	***0.113***	***0.208***	***-0.036***	***-0.342***
South America					
Argentina	0.791 (0.053)	0.160 (0.161)	0.283 (0.167)	0.153	0.010
Brazil	1.22 (0.034)	0.401 (0.158)	0.308 (0.136)	-0.042	-0.501
Chile	1.33 (0.030)	0.235 (0.173)	0.155 (0.139)	-0.478	-1.46
Colombia	1.01 (0.052)	-0.059 (0.188)	0.165 (0.161)	-0.127	-0.495
Costa Rica	1.30 (0.063)	-0.861 (0.298)	-0.189 (0.327)	-0.611	-1.14
Mexico	0.618 (0.024)	-0.154 (0.116)	-0.193 (0.094)	-0.386	-0.616
Peru	0.967 (0.040)	0.101 (0.149)	0.147 (0.135)	-0.081	-0.353
Uruguay	1.18 (0.033)	0.046 (0.203)	0.141 (0.248)	-0.246	-0.754
Mean	***1.05***	***-0.016***	***0.102***	***-0.227***	***-0.664***
East Asia					
Indonesia	0.273 (0.040)	0.534 (0.182)	0.353 (0.186)	0.369	0.386
Japan	0.050 (0.029)	-0.628 (0.206)	-0.613 (0.076)	-0.806	-0.805
Korea	0.650 (0.037)	0.064 (0.188)	0.152 (0.088)	0.005	-0.163
Taiwan	-0.476 (0.028)	-0.545 (0.097)	-0.623 (0.083)	-0.689	-0.756
Thailand	-0.390 (0.063)	-0.491 (0.229)	-0.456 (0.139)	-0.438	-0.420
Vietnam	-0.194 (0.049)	-0.451 (0.284)	-0.756 (0.170)	-0.844	-0.938
Mean	***-0.015***	***-0.253***	***-0.324***	***-0.401***	***-0.449***
Overall mean	***0.664***	***0.005***	***0.017***	***-0.166***	***-0.383***

Note: Clustered standard errors in parentheses in column 3.

Column 3 of Tables 1a and 1b presents the estimated coefficients from multiple linear regressions with standard errors cluster at the school level and using the same model specification. A casual comparison of columns 2 and 3 reveals that the two sets of coefficients are very similar in almost all countries and allow for the same conclusion on the effectiveness of private schools. Differences in the magnitude of estimated coefficients (but not the sign) are found in a small number of countries (for example in the case of Costa Rica).

4.2 The importance of peer groups

The contribution of school peer group effects was evaluated by comparing multiple regressions without and with peer group controls. This contribution varies both between private school types (dependent vs. independent) and between country groups. Table A2 in the Appendix summarizes the controlled effects (from column 3 in Tables 1a and 1b), without and with peer group controls by country grouping.

Accounting for peer effects is particularly important[9] in deriving the independent school effect, as without such peer group controls the average effect would have been about 0.18 of a standard deviation in favour of independent schools, compared to about zero in Table 1b. Peer effects are much more important in Latin American countries (0.42 of a standard deviation in favour of independent schools compared to 0.095); this was also the finding in Somers, McEwan and Willms (2004). On the other hand, in East Asian countries peer effects contribute very little in explaining the private-independent school effect. These findings are consistent with Table 1A in the Appendix, which reported stark differences in quality of peer groups between independent schools and public schools, especially in Latin American countries.

When comparing private-dependent schools to public schools, peer effects are much less important (cross-country average of 0.059 compared to -0.038 of a standard deviation without and with peer group controls), as dependent schools are not much different from public schools in peer group composition; however, in the Latin American group of countries such effects are still important (0.17 compared to -0.043 of a standard deviation without and with peer group controls).

4.3 Bias-corrected estimates of private school effects

[9] Accounting for peer effects can also reduce the extent of selection on unobservables.

Robustness checking in the presence of selection was conducted using assumptions on the value of R_{max} and δ, in order to obtain bounding values of β. Such bounding values can then be compared to the controlled estimates given in column 3 of Tables 1a and 1b (i.e., assuming $\delta = 0$, $R = \tilde{R}$, $\beta = \tilde{\beta}$); R_{max} is bounded between $\tilde{R}$ and 1. As argued in Oster (2015), it is reasonable to assume an $R_{max} < 1$, considering the possibility of measurement error in the dependent variable, Y, or variation in Y which is not related to X, i.e., variation arising from choices made after X is determined.

I use the value of $R_{max} = 1.5\tilde{R}$ without explicitly considering higher values, since any higher value would simply reinforce the conclusions of this study[10]. With respect to the extent of selection on unobservables in relation to observables, I use two alternative values: $\delta = 0.5$ (unobservables are half as important as observables) and equal selection ($\delta = 1$). Between the two, the first which assumes a moderate amount of unobservable selection is more reasonable, since $\delta = 1$ is considered to be an upper bounding value.

Table 1a, column (4) reports the bias-corrected estimates[11,12] of the effect of attending private-dependent schools relative to public schools. With few exceptions, the bias-corrected estimates are lower than the controlled estimates of the private school effect, and generally any negative controlled effect is magnified; over all countries, the estimated effect is negative but small. In the great majority of countries, either no significant effect or a public school advantage is found. However, in a small number of countries private-dependent schools perform better than public schools under both assumptions about the extent of unobservable selection. These are Canada, Indonesia (under equal selection), and possibly Netherlands (with bias-corrected coefficients twice the magnitude of base estimates) and Argentina (under moderate amount of selection.

[10] Here R_{max} is parametrized as: $R_{max} = \min\{\Pi\tilde{R}, 1\}$, with $\Pi = 1.5$.
[11] The Stata program *PSACALC* provided by Emily Oster was used.
[12] Deriving standard errors would require a bootstrap approach, which would depend on the estimator displaying asymptotic normality. The absence of standard errors would be more of a problem in a single country study, but less so for the objectives of the present study.

Table 1b reports the corresponding estimates of the bias-corrected effect for attending independent schools. When we account for selection, even assuming moderate selection, in approximately half of the countries a public school advantage is found, while in several other public schools perform equally well as independent schools. Again, in a very small number of countries the private (independent) school advantage remains robust. These are Belgium, Greece and Indonesia, with some evidence that this may be the case for Jordan. Therefore, despite these few exceptions, there is strong evidence that public schools outperform independent schools in both developed and less developed countries for which data was available.

Looking at the magnitude of the estimated selection bias (difference between base estimates and bias-corrected estimates), as one would expect, the estimated bias tends to be larger for countries with large residual (between school) variance (as reported in Table A3). On the other hand, in countries such as Denmark, Finland, Ireland, Sweden and Taiwan with small residual between variance, base estimates and bias-corrected estimates tend to be of similar magnitude.

4.4 Implications and conclusions

The empirical literature on school choice and effectiveness can be seen as consisting of two distinct strands. One, centred on the voucher programs (see for example, Coleman & Hoffer, 1987; Coleman, Hoffer, & Kilgore, 1982) using predominantly randomized studies, which finds gains for students switching to private schools. The other employs large datasets and suitable methodological approaches (multilevel modelling, IV regression, or other techniques) to account for both observables and selection, with findings which more often than not cast doubt on the existence of a positive private school effect and often point to a negative effect. The present study belongs in the second strand of empirical literature.

The attractiveness of the voucher studies and the consequent perception of a near-consensus that such programs are effective (hence a positive private school effect), can to a large extent be attributed to being randomized. However, there is no lack of criticism and objections to the conclusion that such studies are superior. Lubienski, Weitzel and Lubienski (2009) provide an extensive review of the literature which identifies major weaknesses of such randomized studies, thus refuting claims by school choice advocates that there is a consensus that vouchers for private schools lead to higher academic achievement. These weaknesses relate to: first, problems in properly accounting for selection arising from likely differences in the composition between treated and control groups, as such studies mainly account for observables; and second, inability to account for peer group effects (school level selection bias).

Randomized school choice studies vary widely in their design and are based on a subpopulation of students (those who apply for a voucher), not a population of school children; the fact that parents apply for a voucher on behalf of their child may be associated with unobservable qualities (such a motivation, value placed on education, etc.) which are different from those who do not apply, thus introducing a bias and making it difficult to generalise study findings. Similarly, over time attrition due to some students declining the offered voucher or private schools formally or informally being selective by discouraging less well performing students from applying or enrolling, would make the two groups increasingly different from one-another.

In assessing the effectiveness of (especially large scale) voucher programs from a policy maker's perspective (but not necessarily from parents' perspective), one needs to consider whether a large part of the private advantage found in voucher studies is due to positive spillovers from better peer groups (as some empirical evidence shows); if this is so, the results of such studies are further undermined. As argued in Somers, McEwan and Willms (2004), since the stock of good peers is finite, expanding the private school sector requires enrolling increasingly diverse populations drown from middle and lower income groups, gradually weakening private school effects at the margin.

While there is no ideal methodological approach, this study finds that accounting for both peer effects and selection is necessary when evaluating school effectiveness. Peer effects account for a substantial part of the private-public test score differences, especially in Latin America; not controlling for such effects would overestimate any private school advantage after accounting for observables. This study finds that in OECD, Middle Eastern and Latin American countries, using peer controls eliminates the private-dependent school advantage and severely reduces the estimated independent school advantage, before accounting for selection. On the other hand, accounting for selection (along with controlling for peer effects) is particularly important when comparing public to independent schools; this is because the effect unobservables can be substantial in this comparison.

Private schools are here to stay; some parents are attracted to certain features of private schools and arguably, parents wouldn't care if a school's effectiveness is enhanced by spillovers related to peer group composition, as long as their child benefits from such spillovers. However, evidence on effectiveness of private vs. public schools can be of help to policy makers when designing policies on the extent of public funding for private sector provision and whether such provision is justified. Given the findings of this study (lack of evidence of efficiency differences in favour of private schools), equity considerations should be considered, along with efficiency.

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Appendix

Table A1: Summary statistics of variables of interest by country

Country	(1) % Private	(2) (%) Dependent / Independent schools	(3) % positive peer index (Private-dependent)	(4) % positive peer index (Private-independent)	(5) % positive peer index (Public)
OECD					
Austria*	11.4	n/a	93.9	n/a	49.5
Belgium	70.8	98/2	68.0	100	51.5
Czech Republic	7.8	85/15	64.7	0	51.1
Denmark	16.5	86/14	82.1	97.0	72.0
Finland	5.9	100/0	87.7	-	86.5
France*	20.1	n/a	68.7	n/a	46.3
Germany	6.4	91/9	96.5	100	55.3
Greece	5.2	29/71	100	100	42.2
Hungary	15.3	100/0	45.6	-	36.5
Ireland	60.1	92/8	68.6	95.3	53.4
Italy	4.7	66/34	33.2	87.7	46.7
Netherlands	67.4	98/2	68.6	100	75.2
Poland	8.2	60/40	80.3	100	26.2
Portugal	9.2	61/39	33.4	100	16.0
Slovakia	8.0	93/7	78.1	100	33.3
Spain	38.4	86/14	60.1	84.6	18.8
Sweden	16.6	100/0	85.0	-	77.0
Switzerland	4.2	28/72	96.1	91.8	54.4
United Kingdom	19.6	79/21	84.3	100	69.0
Canada	8.3	52/48	85.2	100	87.0
USA	8.7	10/90	100	98.9	61.1
Australia	38.9	28/72	98.5	91.5	47.5
New Zealand	6.0	0/100	45.0	98.1	51.0
Mean	*19.9*	*68/32*	*74.6*	*81.5*	*52.5*
MENA					
Jordan	11.1	4/96	0	57.5	9.0
Qatar	38.0	2/98	100	92.2	76.4
UAE	57.5	27/73	91.3	88.9	45.7
Mean	*35.5*	*11/89*	*63.8*	*79.5*	*43.7*
South America					
Argentina	36.5	77/23	49.1	71.3	6.4
Brazil	14.3	27/73	47.3	56.3	0.7
Chile	71.7	57/43	23.4	94.1	1.9
Colombia	20.7	45/55	21.2	58.0	0.6
Costa Rica	14.1	40/60	65.8	84.6	1.7
Mexico	12.3	21/79	66.4	68.1	3.7
Peru	20.8	22/78	18.3	25.5	0.7
Uruguay	16.5	0/100	-	38.2	0.9
Mean	*25.9*	*36/64*	*41.6*	*62.0*	*2.1*
East Asia					
Indonesia	40.5	44/56	0	4.3	1.0
Japan	27.7	0/100	-	67.6	31.2
Korea	47.1	66/34	34.3	81.7	53.7
Taiwan	40.5	13/87	0	25.5	19.6
Thailand	12.5	71/29	0	12.4	17.2
Vietnam	8.2	0/100	-	0	1.5
Mean	*29.4*	*32/68*	-	*31.5*	*20.7*
Overall mean	***23.7***	***51/49***	***65.4***	***73.4***	***37.0***

Note: No information is available on proportion government-dependent private schools for Austria and France.

Table A2: Controlled private school effects without and with peer group controls

	Private-dependent vs. Public schools		Independent vs. Public schools	
	Without	**With**	**Without**	**With**
OECD	0.101	0.010	0.204	0.064
MENA	-	-	0.330	0.165
South America	0.168	-0.043	0.417	0.095
East Asia	-0.340	-0.249	-0.315	-0.332
Overall mean	***0.059***	***-0.038***	***0.172***	***0.007***

Table A3: Multilevel regressions: random intercept variance estimates – full model

Austria		**USA**	
Variance (constants)	0.165 (0.026)	Variance (constants	0.094 (0.024)
Variance (residuals)	0.420 (0.013)	Variance (residuals)	0.609 (0.018)
Variance partition coefficient	0.282	Variance partition coefficient	0.134
Observations	4,676	Observations	4,880
Number of schools	165	Number of schools	153
Belgium		**Australia**	
Variance (constants)	0.147 (0.017)	Variance (constants)	0.102 (0.011)
Variance (residuals)	0.406 (0.011)	Variance (residuals)	0.588 (0.011)
Variance partition coefficient	0.266	Variance partition coefficient	0.148
Observations	8,400	Observations	14,342
Number of schools	269	Number of schools	745
Czech Republic		**New Zealand**	
Variance (constants)	0.110 (0.014)	Variance (constants)	0.047 (0.009)
Variance (residuals)	0.410 (0.013)	Variance (residuals)	0.620 (0.016)
Variance partition coefficient	0.211	Variance partition coefficient	0.070
Observations	5,068	Observations	4,216
Number of schools	244	Number of schools	168
Denmark		**Jordan**	
Variance (constants)	0.046 (0.008)	Variance (constants)	0.227 (0.042)
Variance (residuals)	0.603 (0.015)	Variance (residuals)	0.547 (0.015)
Variance partition coefficient	0.071	Variance partition coefficient	0.293
Observations	7,436	Observations	7,038
Number of schools	329	Number of schools	233
Finland		**Qatar**	
Variance (constants)	0.033 (0.011)	Variance (constants)	0.094 (0.016)
Variance (residuals)	0.640 (0.017)	Variance (residuals)	0.419 (0.016)
Variance partition coefficient	0.049	Variance partition coefficient	0.183
Observations	8,622	Observations	10,785
Number of schools	292	Number of schools	143
France		**UAE**	
Variance (constants)	0.147 (0.017)	Variance (constants)	0.155 (0.015)
Variance (residuals)	0.351 (0.011	Variance (residuals)	0.446 (0.010)
Variance partition coefficient	0.295	Variance partition coefficient	0.258
Observations	4,487	Observations	10,622
Number of schools	216	Number of schools	391
Germany		**Argentina**	
Variance (constants)	0.158 (0.023)	Variance (constants)	0.146 (0.018)
Variance (residuals)	0.384 (0.013)	Variance (residuals)	0.412 (0.012)
Variance partition coefficient	0.291	Variance partition coefficient	0.257
Observations	4,203	Observations	5,753
Number of schools	220	Number of schools	219
Hungary		**Brazil**	
Variance (constants)	0.132 (0.016)	Variance (constants)	0.219 (0.023)
Variance (residuals)	0.345 (0.012)	Variance (residuals)	0.479 (0.012)
Variance partition coefficient	0.277	Variance partition coefficient	0.314

Observations Number of schools	4,682 164	Observations Number of schools	17,987 724
Greece Variance (constants) Variance (residuals) Variance partition coefficient Observations Number of schools	 0.149 (0.033) 0.567 (0.015) 0.208 4,867 161	**Chile** Variance (constants) Variance (residuals) Variance partition coefficient Observations Number of schools	 0.090 (0.015) 0.413 (0.011) 0.179 6,788 200
Ireland Variance (constants) Variance (residuals) Variance partition coefficient Observations Number of schools	 0.033 (0.008) 0.707 (0.024) 0.045 4,681 171	**Colombia** Variance (constants) Variance (residuals) Variance partition coefficient Observations Number of schools	 0.143 (0.016) 0.518 (0.014) 0.216 8,969 325
Italy Variance (constants) Variance (residuals) Variance partition coefficient Observations Number of schools	 0.251 (0.018) 0.435 (0.009) 0.366 30,528 1,064	**Costa Rica** Variance (constants) Variance (residuals) Variance partition coefficient Observations Number of schools	 0.149 (0.032) 0.472 (0.016) 0.240 4,441 186
Netherlands Variance (constants) Variance (residuals) Variance partition coefficient Observations Number of schools	 0.267 (0.084) 0.259 (0.009) 0.508 4,288 174	**Mexico** Variance (constants) Variance (residuals) Variance partition coefficient Observations Number of schools	 0.230 (0.016) 0.573 (0.011) 0.286 32,351 1,223
Poland Variance (constants) Variance (residuals) Variance partition coefficient Observations Number of schools	 0.060 (0.010) 0.626 (0.016) 0.087 4,553 169	**Peru** Variance (constants) Variance (residuals) Variance partition coefficient Observations Number of schools	 0.149 (0.017) 0.450 (0.014) 0.249 5,939 219
Portugal Variance (constants) Variance (residuals) Variance partition coefficient Observations Number of schools	 0.090 (0.016) 0.556 (0.016) 0.139 5,523 190	**Uruguay** Variance (constants) Variance (residuals) Variance partition coefficient Observations Number of schools	 0.109 (0.018) 0.503 (0.016) 0.178 5,045 168
Slovakia Variance (constants) Variance (residuals) Variance partition coefficient Observations Number of schools	 0.139 (0.016) 0.421 (0.013) 0.248 4,454 190	**Indonesia** Variance (constants) Variance (residuals) Variance partition coefficient Observations Number of schools	 0.272 (0.033) 0.395 (0.011) 0.408 5,530 197
Spain Variance (constants)	 0.082 (0.007)	**Japan** Variance (constants)	 0.155 (0.029)

Variance (residuals)	0.653 (0.010)	Variance (residuals)	0.434 (0.016)
Variance partition coefficient	0.111	Variance partition coefficient	0.263
Observations	25,048	Observations	6,318
Number of schools	874	Number of schools	190
Sweden		**Korea**	
Variance (constants)	0.050 (0.009)	Variance (constants)	0.098 (0.017)
Variance (residuals)	0.667 (0.016)	Variance (residuals)	0.627 (0.034)
Variance partition coefficient	0.070	Variance partition coefficient	0.135
Observations	4,565	Observations	5,033
Number of schools	184	Number of schools	156
Switzerland		**Taiwan**	
Variance (constants)	0.122 (0.014)	Variance (constants)	0.047 (0.011)
Variance (residuals)	0.533 (0.013)	Variance (residuals)	0.592 (0.026)
Variance partition coefficient	0.186	Variance partition coefficient	0.074
Observations	11,037	Observations	6,046
Number of schools	371	Number of schools	160
UK		**Thailand**	
Variance (constants)	0.115 (0.015)	Variance (constants)	0.229 (0.062)
Variance (residuals)	0.640 (0.018)	Variance (residuals)	0.345 (0.012)
Variance partition coefficient	0.152	Variance partition coefficient	0.399
Observations	12,659	Observations	6,466
Number of schools	507	Number of schools	210
Canada		**Vietnam**	
Variance (constants)	0.115 (0.012)	Variance (constants)	0.260 (0.045)
Variance (residuals)	0.706 (0.012)	Variance (residuals)	0.396 (0.017)
Variance partition coefficient	0.140	Variance partition coefficient	0.396
Observations	20,941	Observations	4,909
Number of schools	808	Number of schools	156