Private, Private Government-Dependent and Public schools. An International Efficiency Analysis using Propensity Score Matching

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IRES-ECON-UCL
August 03

Abstract: This paper aims at estimating the effect on achievement of various types of schools: private, private but government-dependent and public ones. It is based on the analysis of Math, Science and Reading test scores of 15 year-olds students surveyed in 2002 across OECD and non-OECD countries. The estimation of the effect of private vs. public school attendance may be biased by the existence of confounding factors. An obvious start is to use standard (OLS) models to isolate the effect of private/public status from the other determinants of achievement like family resources or socio-economic background. But OLS estimates are highly dependent on the validity of the linearity assumption i.e. that the effect of school type is uniform across the distribution of covariates. Hence, the rational for using non-parametric propensity score matching. The main result is that in most countries examined, the type of school has so statistically significant impact on achievement. There is a small group of countries where students attending private schools (UK, Brazil) or private government-dependent schools (French-Speaking Belgium, France and Ireland) clearly perform better than those attending public schools. But there are also cases like Switzerland and Austria where private schools appear less efficient than public schools.

JEL classification: I28 (Education: Government Policy). H520 (National Government Expenditures and Education).

Keywords: education economics, human capital, resource allocation, school choice, multiple treatments evaluation, propensity score

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Introduction

It is clear that the production of education requires monetary resources. Yet, several studies (e.g. Hanushek, 1986; Hanushek, 2000) have repeatedly highlighted over the last two decades the fact that there is no mechanical relationship between the level of public spending and pupils' results. In this context, economists and other social scientists have come to consider that more attention should be paid to the organizational characteristics of schools, in particular whether it makes a difference that they are privately run or funded or directly governed by central or local public authority. Is there some (robust) evidence that students could gain/loose by transferring from a public to a private school? And if so, what is the magnitude of the differential?

The study of existing education systems can provide part of the answer to this question. Indeed, in many countries around the world, production of education is far from being a public monopoly. It is thus not a real surprise that both private and public schools are represented in the latest OCDE survey on academic achievement used in this paper. We are here referring to the Program for International Student Assessment (PISA). This survey, carried out in 2000, is aimed at testing the competencies in Math, Sciences and Reading of representative samples of 15 year-olds students across OCDE and non-OECD countries[1]. The resulting data set is very rich and can be used to address many questions relevant to education policy, one of them being the presence and the magnitude of a private/public achievement differential.

To avoid any confusion, the reader should take good note of the way private/public categories are defined by the OECD and also the logic underlying this classification. A school was first classified as either public or private according to whether a public agency or a private entity had the ultimate decision-making power concerning its affairs. A school is public if the principal reported that it was managed directly or indirectly by a public education authority, government agency, or by a governing board appointed by government or elected by public franchise. A school is considered as private if the principal reported that it was managed directly or indirectly by a non-government organisation (e.g., a church, a trade union, business or another private institution).

But not all privately managed school are privately funded as often assumed. In the Netherlands, and to a lesser extent in Belgium, Ireland, Spain, or Denmark, significant portions of the student/pupil population attend schools operated by non-profit private boards largely (up to 90%) funded by public money. The Catholic and Protestant churches for example have been very active in establishing private schools. The point is that are now largely integrated into the public system via the public funding mechanism. This specificity should be accounted for in an analysis aimed at comparing the efficiency of various types of schools. A distinction needs to made between government-dependent and independent private schools according to the degree of dependence on government funding.

In the OECD survey school principals were asked to specify the percentage of the school's total funding received in a typical school year from: government sources; student fees or school charges paid by parents; benefactors, donations, bequests, sponsorships or parental fund-raising; and other sources. Schools were classified as government-dependent private if they received 50 per cent or more of their core funding from government agencies and independent private if they received less than 50 per cent of their core funding from government agencies.

In brief, this means that in the rest of the paper will try to assess the relative efficiency of tree types of schools: private government independent (less that 50% of public funding), private government dependant (more than 50% of public funding) and public schools.

This paper is organized in 4 sections. Section 1 briefly exposes our theoretical framework i.e. the education production function we attempt to estimate, as well as the different categories of variables and biases that must be accounted for in order to isolate a true private/public effectiveness differential. It also contains the empirical strategies used to estimate these models. Section 2 presents the international data set we use, while Section 3

[1] Australia, Austria, Belgium (French-Speaking), Belgium (Dutch-Speaking), Brazil, Canada, China, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, Hong Kong China, Korea, Latvia, Luxembourg, Mexico, The Netherlands, New Zealand, Norway, Poland, Portugal, Russian Federation, Spain, Sweden, Switzerland, United Kingdom, United States.

contains the results of our empirical analysis that we confront to those of previous studies. The last section aims at exploring and discussing the potential causes of private-public efficiency differentials.

1. Education Production Function with Private/Public school effect: presentation and generic problems

Following Summers & Wolfe (1977) and Toma & Zimmer (2000), we use test scores as a measure of output. We assume that academic achievement, at any time period t, is a function of family and school resources, of the student's peers[2], and of the student's individual characteristics. Conceptually, the model to be estimated at any time period t is:

$$A = f(X) \qquad (1.)$$

Where A = student's achievement, X= vector of school monetary resources or proxies, student's characteristics, including family/social background, and some characterization of the group of peers.

OLS parametric model

Following McEwan (2001) and Greene (2000), we hypothesize that student *i*'s achievement (*A*) in a particular country can be explained by linear models of the following form:

$$A=X\alpha + \delta PRIV + \gamma PRIVGD +\varepsilon \qquad (2.)$$

where *PRIV* is a dummy variable indicating whether or not the *i*th students attended private government independent school and *PRIVGD* reflecting attendance of a private but government-dependent school.

If the independent variables (*X*) perfectly control for the student background, then estimating the preceding equation with Ordinary Least Squares (OLS) could yield unbiased estimates. The estimated value for coefficient δ and γ should capture the effectiveness differential between private, private government dependant and public schools (serving as reference here and after).

The focus of rest of the paper will be on the sensitivity of these OLS results to relaxation of the assumption of the linearity of the private-public effect.

Propensity Score Matching:

One of the drawbacks of OLS is that it is dependent on the validity of the linearity assumption underlying equation (2). In this expression private-public management effect is supposedly uniform across the distribution of covariates and it is assumed to be adequately captured by a dummy variable. Nothing is less certain.

Following Rosenbaum & Rubin (1983; 1985) we therefore complement our OLS model with the non-parametric matching approach, potentially more robust to departure from linearity. The underlying principle consists of matching together treatment (i.e. pupils attending private or private government schools) and comparison units (pupils attending public schools) that are similar in terms of their observable characteristics. This method, like the

[2] We indeed assume child's ability to acquire formal knowledge is influenced by the characteristics of his/her peers. Formal education inevitably takes place in classrooms where students are together and interact. In turn, these classrooms are part of a school where students tend also to interact, generating what pedagogues call peer effects (Slavin, 1987 ; Grisay, 1993 ; Gamoran & Nystrand, 1994), sociologists contextual effects (Coleman, 1966, 1988; Jencks & Meyer, 1987; Willms & Echols, 1992) and economists social externalities (Henderson, Mieskowski & Sauvageau, 1978 ; Hanushek, 1986 ; Brueckner & Lee, 1989 ; Bénabou, 1993, 1996 ; Glewwe, 1997; Vandenberghe, 2002).

OLS, comes however at a certain cost as it is based on a very strong assumption: the relevant differences between treatment and comparison observations must be fully embedded in the set of observable covariates. Under this condition (often reported as the Conditional Independence Assumption, or CIA) estimators relying on matching techniques can yield i) unbiased estimates of the treatment ii) that are not dependent on potentially irrelevant parametric assumptions (linearity...)

One could match pupils directly on their vector of covariates (i.e. individuals could be stratified into bins, each of them characterised by a particular value of X_i). This method however is difficult to implement if the number of covariates to control for is large. The number of cells into which the data has to be divided will augment exponentially. But Rosenbaum and Rubin (1983, 1985) suggested a clever way to overcome this problem. They actually demonstrate that matching can be done on a single-index variable (the propensity score estimated by probit/logit models) that considerably reduces the dimensionality problem, because the conditioning is on a scalar rather than on a vector.

Yet, given the nature of our problem (comparing the efficiency of three types of schools), the framework developed by Rosenbaum & Rubin for a two-types situation (treated vs. non-treated) need first to be generalized. Fortunately for us this has already been done by Lechner (2000) and applied in the context of labour market program evaluation by Sianesi (2001).

Lecher & Sianesi assume a set of k different kinds of mutually exclusive treatments[3] be available to individual i. In the context of this paper the choice set of a student and his/her family may contain 2 types of private school (private & private government dependant) as well as a public school option. In some countries like Belgium or Denmark, it might be the case that the set of choice is more limited containing only two possibilities : a public school or one of the two types of private schools (private government-dependent in the case of Belgium). In the later case, the Lechner-Sianesi model simplifies an can be equated to the original propensity score matching model developed by Rosenbaum & Rubin.

Interest lies in the causal average effect of a treatment relative to another treatment on achievement. A set of potential outcomes is correspondingly associated to each of the potential treatments: A_0, A_1,... A_k, with $A_{,k}$ denoting achievement for individual i receiving treatment k. Let $T\{0, 1, \ldots, K\}$ denote the actual assignment to a specific treatment (i.e. attendance of a certain type of school), so that T_i=k if individual i attends type k school.

In what follows, the focus will be on the generalisation of the 'effect of treatment on the treated' : the equivalent of treatment effect captured by dummies (δ and γ) in equation 2: the pair-wise comparisons of the average effect of treatment k relative to treatment k' conditional on assignment to treatment k, for all combinations of k and k':

$$E(A_k - A_{k'}|T=k) = E(A_k|T=k) - E(A_{k'}|T=k) \text{ for } k, k'\{0, 1, \ldots, K\}, k\ \overline{k}' \qquad (3.)$$

The first term of equation (3) -- the average outcome following treatment k for individuals who have participated in k -- is observed in the data. But it is not the case of the counterfactuals of the type $E(A_{k'}|T=k)$, i.e. all the outcomes participants in k would have experienced, on average, had they taken any treatment other than k. Identifying assumptions thus need to be invoked to overcome this fundamental missing data problem. One such assumption often invoked in evaluation exercises is the conditional independence assumption (CIA). It requires the existence of a set of observable characteristics X such that, conditional on their values X=x, the treatment indicator T is independent of the entire set of potential outcomes.

$$T \perp (A_0, A_1, \ldots, A_K) \,|\, X=x, \ \forall \ x \in C^* \qquad (4.)$$

C^* being the set of X values for which the treatment effect is defined

[3] In fact they assume the stable-unit-treatment-value (SUTVA) assumption has to be fulfilled, requiring the potential outcomes for the individual $i$just depend on the treatment she received. That is, there is "no interference between units" and there are "no versions of treatments".

Since we are just interested in the pair-wise comparison of the various kinds of treatments (i.e. private vs. public or private government-dependent vs. public schools), we can relax strong CIA by requiring conditional independence to hold only for the sub-populations receiving either treatment *k* or treatment *k'* (Lechner, 2000): all the (outcome-relevant) differences between individuals choosing treatment *k* and those selecting into treatment *k'* need to be captured by covariates the evaluator can control for.

$$T \perp (A_k, A_{k'}) \mid X=x, \ \forall \ x \in C^*, T \in \{k, k'\} \text{ for } k, k' \in \{0, 1, \ldots, K\}, k>k' . \qquad (5.)$$

The unobserved counterfactuals can thus be identified as:

$$E(A^{k'}|T=k) = E_X\,[E(A^{k'}|T=k, X)|T=k] = E_X[E(A^{k}\,|T=k', X)|T=k] \qquad (6.)$$

where the inner expectation is identified due to CIA and the outer expectation is taken with respect to the distribution of X for participants in k. One could match pupils directly on their vector of covariates (i.e. individuals could be stratified into bins, each of them characterised by a particular value of X. This method however is difficult to implement if the number of covariates to control for is large. The number of cells into which the data has to be divided will augment exponentially. But Rosenbaum and Rubin (1983, 1985) suggested a clever way to overcome this problem. For the single treatment case ($T\in \{0,1\}$) they show that the propensity score

$$Pr(T=1|X) \equiv P^{k=1}(X) \qquad (7.)$$

provides a parsimonious way to adjust for differences in a set of pre-treatment characteristics (X) between treatment and non-treatment groups. They actually demonstrate that matching can be done on a single-index variable estimated by probit/logit models that considerably reduces the dimensionality problem, because the conditioning is on a scalar rather than on a vector.

But we are in a multi treatment context. Can propensity scores still be used to solve the dimensionality problem? Lechner (2000) demonstrates that is can. When interested by pair-wise comparisons of the various treatments, the conditioning variable (balancing score) of minimal dimension which ensures the balancing of observables X in the two sub-populations of interest k and k' is thus still given by a scalar: the conditional choice probability of treatment k given either treatment k or k':

$$P^{k|kk'}(X)= \frac{\Pr(T=k|X)}{\Pr(T=k|X)+\Pr(T=k'|X)} \equiv \frac{P^{k}(X)}{P^{k}(X)+P^{k'}(X)} \qquad (8.)$$

Under the CIA, the required counterfactual (equation 6) can thus be estimated as follows

$$E(A^{k'}|T=k) = E_X[E(A^{k}\,|T=k', P^{k|kk'}(X))|T=k] \qquad (9.)$$

For any pair of treatments k and k', under the CIA assumption that all the outcome-relevant differences between the two groups are captured by their observable characteristics X, the average outcome experienced by the matched pool of k'-participants thus identifies the counterfactual outcome participants in k would have experienced, on average, had they taken treatment k' instead.

Any standard probability model can be used to estimate the conditional choice probabilities $P^{k|kk'}(X)$. We have opted for a multinomial logit model to calculate predicted probabilities of a respondent being in a certain type of school, and then computed conditional scores *per se*.

Before proceeding to matching, it is necessary to ensure that any combination of characteristics seen among those in the treatment group may also be observed among those in the non-treatment group. In order to adjust for differences in X, sufficient overlap is required in the distribution of X by treatment status. In propensity terms the so-called common support requirement for all pair-wise conditional parameters translates into:

$0 < P^{k|kk'}(X) < 1$ for $X \in C^*$ and k=0, 1, …, K (10.)

If there are regions where the support of X does not overlap for the two groups, matching has to be performed over the common support region. And the estimated treatment effect has then to be redefined as the mean treatment effect for those treated k falling within the common support.

Finally, even with common support the probability of observing two pupils with exactly the same value of $P^{k|kk'}(X)$ is in principle zero since $P^{k|kk'}(X)$ is a continuous variable. Various methods have been proposed in the literature to overcome this difficulty. We have opted here for the so-called *nearest neighbour* matching approach. It consists of an algorithm that matches each pupil attending a type k school with his/her type k' school peer displaying the nearest propensity score.

2. Data set and estimation strategy

Data and variable categories

The data we use to assess the impact of type of school on achievement is relatively unique and fairly recent. It comes from the 2000 OECD survey (the so-called PISA project, Program for International Student Assessment). This database contains math, science and reading test scores of students aged 15 across 34 OECD and non-OECD countries. These students are nested within schools, potentially attending different grades in countries with grade repetition. The test score variable has been normalized[4] to have mean 1 and variance 0. To carry out our analysis, we only selected countries for which the number of students sampled and attending private school is above a 1% threshold and superior or equal to 50. This leads to a subset of 23 countries or regions containing AUSTRIA, French-Speaking Belgium (BEL_FR), Dutch-Speaking Belgium (BEL_D), BRAZIL, Czech Republic (CZ), DENMARK, FINLAND, FRANCE, GERMANY, GREECE, HUNGARY, IRELAND, ITALY, JAPAN, LUXEMBOURG, MEXICO, NETHERLANDS, New Zealand (NZ), SPAIN, SWEDEN, SWITZERLAND, the UK and the USA[5]. Justifications for this restriction are twofold. First, it makes no sense, statistically speaking, to assess a private school effect in a particular country using test scores of just of few dozen students. Second, policy-makers who currently discuss the opportunity to expand the private sector (using vouchers for example) are interested in knowing whether private or private government-dependent schools make a difference when attended by a large (and heterogeneous) population. We are tempted to add that the second argument suggests paying more attention to countries for which the (sample) share of private education is large[6], as in Belgium or the Netherlands where more than 50% of secondary school students attend a private school.

Table 1 below gives the students' repartition between public, private and private government-dependent schools, by country, for each one of the PISA samples we used (Mathematics, Reading and Sciences).

[Insert Table 1 about here]

Referring to equation (1) in section 1, we have selected information about school inputs via self-reported information regarding the availability of teaching material. We use answers provided by heads of school to build dummy identifying schools with lack of teaching material (*LCTMAT*)

The data set (see table 2 for descriptive statistics) is relatively rich in terms of individual characteristics and family socio-economic background/status; information that are known to affect academic achievement. We retained besides gender (*GIRL*), the birth order of the student (*BRTHORD*=1 if student is first born), the highest degree of mother *(MISCED=1* if she completed some post-secondary degree, *MISCED*=0 otherwise) the immigration status of father (*FATHIM=1* if father born outside country of test, *FATHIM=0* otherwise), the highest socio-economic index of the two parents (*HISEI*) [7] as well as an index of cultural resources available at home (*HEDRES*) [8].

[Insert Table 2 about here]

Of great interest is the peer effect. We define it as *the average* parental socio-economic index of the student' schoolmates (PHISEI), assuming that the peer effect is better captured by the socio-economic mix of the peer group.

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[4]Normalisation to mean ***M*** and standard deviation ***S***, simply transforming x to y with formula y= ***S****(x-E(x))/Sx + ***M***

[5] We excluded KOR due to important missing data frequency among the variables of interest. We also excluded POLAND and PORTUGAL because these countries only report results for reading.

[6] Assuming that the PISA sample is representative of the private/public division in reality.

[7] The last variable is the result of the conversion of Isco-88 (International Standard Classification of Occupations) into International Socio-economic Index of Occupational Status (ISEI). For further details see http://www.fss.uu.nl/soc/hg/pisa/index.htm

[8] The last variable is built by the authors following using several items available in the surveys. Technically speaking it constists of the estimate of an implicit variable using an Item Response Model and a Maximum Likelyhood algorithm.

Finally, private schools are identified by dummy variables (*PRIV, PRIVFG*) equal to 1 by contrast to the public schools for which these dummies equals 0.

Estimation strategy

We logically focus on the magnitude of the private/public an private government-dependent/public school differential. We first measure gross differentials. We do so simply by comparing the mean values of math, science and reading test scores of students for each type of school (the gross differential being equal to private mean minus public mean). Using the different independent variable potentially explaining academic results we then run the traditional OLS models to get a first estimate of net private school effect i.e. accounting for level of resources, socio-economic status and peer endowments.

The second and more consequent step is to implement the propensity score approach developed in section 1 using the same set of control variables i.e. *GIRL, LCTMAT, MISCED, FATHIM HISEI, HEDRES, PHISEI.*

3. Results and analysis

In Tables 5-7 below, we present into great details the three types of results of interest: [1] the gross score differential between private, private government-dependent and public students, [2] the coefficient associated to the *PRIV* and *PRIVGD* dummy *(δ, γ)* in an OLS regression model,[3] the estimates of the Average Treatment of the Treated (ATT) -- in other words, the effect of attending a private school -- with propensity score matching using a nearest neighbour algorithm.

[Insert Tables 5-6 about here]

Table 7 and 8 contains information useful to evaluate the quality of matching obtained with our propensity score model. It displays the degree of balancing of covariates before and after propensity score matching. These help us pinpoint the problematic case of New Zealand where the propensity matching model we used fails to reduce the level of asymmetry between covariates.

[Insert Tables 7-8 about here]

Table 9 recapitulates the results obtained with the estimation method we trust most: the propensity score matching model.

Results per se are essentially fourfold.

First, in most countries examined in this study, the type of school (private, private but government-dependent, public) has so statistically significant impact on achievement.

Second, there is a small group of countries where students attending either private schools (UK, Brazil) or private government-dependent schools (French-Speaking Belgium, France and Ireland) clearly perform better than those attending public schools. Differentials are statistically significant and of great magnitude. Table 9 suggests for example that in Brazil private school outperform public ones by 38% of a standard deviation, in French-Speaking Belgium by 31%, an by 20% in France.. But there are also cases like Switzerland and Austria where private schools appear significantly less efficient than public schools by respectively 55% and 33% of a standard deviation. Compared with the size of estimates generally obtained in the education production function literature, these (positive and negative) effects can be considered as sizeable

Third, topics (math, reading, science) matter less than countries. In other words, within a country private, private government-dependent vs. public differences tend to appear with similar sign and magnitude for each of the three topics. But not all countries display differences between types of schools.

Fourth, a closer look at table 9 suggests there is a systematic advantage to private government-dependent schools compared to private schools. But only within countries where both types of privately owned schools exists (Austria, France, Ireland, Spain and Switzerland).

[Insert Tables 9 about here]

4. Further thoughts

Results presented here indicate that private or private government-dependent education can have a significant -- positive or negative -- effect on 15 year-olds' academic achievement. This was shown here using math, reading literacy and science test scores. But it is worth commenting the results into more details. In fact this conclusion is only valid for some countries. In the UK and Brazil, private schools outperform public schools. In French-Speaking Belgium, France and to a lesser extent Ireland, the efficiency premium goes to private government-dependent schools. By contrast, Switzerland and Austria are example of countries where private school perform less well than public schools. But for most countries examined here we would rather conclude to the absence of systematic advantage to private or private government-dependent schools. Finally, it might be worth noticing than in the few countries where both private and private government-dependent schools coexist, the later are more efficient than the former.

If private or private government-dependent schools (positive and negative) effects holds only for some countries, how can they be explained? And similarly how can one explain that in some other countries privately run schools seem to be no more (less) efficient than public ones? Two alternatives, sometimes conflicting, interpretations coexist to explain private, private government dependant vs. public effect. The first interpretation, which would be favoured by economists, is that the private and public dichotomy in fact points to regulation differences. This is the “organizational” interpretation of achievement difference. Following this line of reasoning, private school in the UK, Brazil, the French-Speaking community of Belgium, or Ireland could possibly perform better because they are granted more autonomy. And maybe private schools have no more autonomy than public ones in all the other countries.

The problem with that interpretation is that is doesn't fit very well with our results. It is indeed hard to reconcile the 'more autonomy-more efficiency assumption' with the poor performance of private schools in Switzerland and Austria (bottom of table 9), and – more importantly -- the fact that in the countries where both private and private government-dependent schools coexist, the later – presumably less autonomous -- are more efficient than the former.

This leads us to a second more cultural interpretation of private/public school differential suggested by McEwan (2000) or Dronkers & Roberts (2003). Rather than talking about “private schools” effects, it might make more sense – at least in some countries like Ireland, Belgium -- to talk about “religious” schools effect. Indeed, some private schools and a majority of private government-dependent schools are, *in fine*, run by religion-affiliated boards (Mc Ewan refers to Catholic Schools in Latin America, Dronkers & Roberts to Protestant Schools in Northern Europe). According to this cultural interpretation, the better education received in private or private government-dependent schools could be explained by religious values. In fact, the main religions enhance values such as hard work, effort, obedience, discipline, and dedication to a task for both students and teachers (maybe also parents). This is a very seductive interpretation that tend to fit better to our results than the previous one. But it also has its limits. Results presented in this paper suggest indeed that private government-dependent schools in the Netherlands or Germany for example, do not outperform public one. But it is an undisputable fact that most of private government-dependent schools in those two countries are religion-affiliated.

Further research is needed to explore these two categories of assumptions and maybe other ones. This means that we need more detailed data about regulatory environment and management style of both public and private schools in countries in which these two types of school cohabit. And as regards private school, following Mc Ewan's remarks, we would also need to distinguish private schools with a religious affiliation (catholic, protestant, ...), those that are secular or simply for-profit.

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Table 1 - Number of students, breakdown by country and type of school (public/private/private government-dependent) + category of country according number of types of private schools

Country	Country cat!	topic	#PRIV	#PRIVGD	#PUB	%PRIV	%PRIVGD	%PUB
AUSTRIA	PRIVfg	math	142	134	2228	0.06	0.05	0.89
		read	253	240	4008	0.06	0.05	0.89
		scie	137	140	2254	0.05	0.06	0.89
BEL_FR	PRIVg	math		1017	432	0.00	0.70	0.30
		read		1800	766	0.00	0.70	0.30
		scie		1012	413	0.00	0.71	0.29
BEL_D	PRIVg	math	17	1629	485	0.01	0.76	0.23
		read	32	2900	814	0.01	0.77	0.22
		scie	18	1613	468	0.01	0.77	0.22
BRAZIL	PRIVf	math	241		1956	0.11	0.00	0.89
		read	429		3527	0.11	0.00	0.89
		scie	243		1950	0.11	0.00	0.89
CZ	PRIVg	math	12	174	2861	0.00	0.06	0.94
		read	21	313	5003	0.00	0.06	0.94
		scie	12	175	2860	0.00	0.06	0.94
DENMARK	PRIVg	math		523	1731	0.00	0.23	0.77
		read		929	3082	0.00	0.23	0.77
		scie		515	1713	0.00	0.23	0.77
FINLAND	PRIVg	math		87	2616	0.00	0.03	0.97
		read		150	4714	0.00	0.03	0.97
		scie		82	2628	0.00	0.03	0.97
FRANCE	PRIVfg	math	177	324	1772	0.08	0.14	0.78
		read	321	581	3178	0.08	0.14	0.78
		scie	177	325	1760	0.08	0.14	0.78
GERMANY	PRIVg	math		109	2364	0.00	0.04	0.96
		read		188	4254	0.00	0.04	0.96
		scie		105	2388	0.00	0.04	0.96
GREECE	PRIVf	math	83		2425	0.03	0.00	0.97
		read	145		4353	0.03	0.00	0.97
		scie	80		2416	0.03	0.00	0.97
HUNGARY	PRIVg	math	17	116	2568	0.01	0.04	0.95
		read	32	201	4500	0.01	0.04	0.95
		scie	17	112	2575	0.01	0.04	0.95
IRELAND	PRIVfg	math	58	1267	770	0.03	0.60	0.37
		read	109	2279	1405	0.03	0.60	0.37
		scie	59	1264	778	0.03	0.60	0.37
ITALY	PRIVf	math	103	14	2484	0.04	0.01	0.96
		read	190	29	4468	0.04	0.01	0.95
		scie	106	17	2482	0.04	0.01	0.95
JAPAN	PRIVf	math	836	18	2047	0.29	0.01	0.71
		read	1513	32	3672	0.29	0.01	0.70
		scie	843	17	2033	0.29	0.01	0.70
LUXEMBOURG	PRIVg	math		200	1619	0.00	0.11	0.89
		read		373	2878	0.00	0.11	0.89
		scie		205	1584	0.00	0.11	0.89
MEXICO	PRIVf	math	324		1970	0.14	0.00	0.86
		read	584		3521	0.14	0.00	0.86
		scie	323		1952	0.14	0.00	0.86
NETHERLANDS	PRIVg	math		936	307	0.00	0.75	0.25
		read		1698	548	0.00	0.76	0.24

		scie		953	301	0.00	0.76	0.24
NZ	PRIVf	math	83	1	1840	0.04	0.00	0.96
		read	152	2	3302	0.04	0.00	0.96
		scie	86	1	1824	0.05	0.00	0.95
SPAIN	PRIVfg	math	268	940	2000	0.08	0.29	0.62
		read	491	1705	3622	0.08	0.29	0.62
		scie	273	958	2009	0.08	0.30	0.62
SWEDEN	PRIVg	math		84	2380	0.00	0.03	0.97
		read		154	4262	0.00	0.03	0.97
		scie		85	2359	0.00	0.03	0.97
SWITZERLAND	PRIVfg	math	129	58	3004	0.04	0.02	0.94
		read	223	108	5416	0.04	0.02	0.94
		scie	127	58	3020	0.04	0.02	0.94
UK	PRIVf	math	231		4601	0.05	0.00	0.95
		read	421		8255	0.05	0.00	0.95
		scie	235		4581	0.05	0.00	0.95
USA	PRIVf	math	57	17	1569	0.03	0.01	0.95
		read	106	30	2811	0.04	0.01	0.95
		scie	59	15	1546	0.04	0.01	0.95

!Country category: PRIV: only private schools, PRIVGD: only private government-dependent schools; PRIV/PRIVGD: private and private government-dependent schools
Source: PISA (2000)

Table 2 – Summary statistics: math (Mean. *Standard Deviation*)

Country	girl	lctmat	brthord	misced	fathim	hisei	hedres	phisei
AUSTRIA	0.50	0.10	0.36	0.65	0.12	48.96	0.26	49.02
	0.50	*0.29*	*0.48*	*0.48*	*0.33*	*14.03*	*0.79*	*7.50*
BEL_FR	0.51	0.23	0.31	0.63	0.28	50.25	0.07	50.11
	0.50	*0.42*	*0.46*	*0.48*	*0.45*	*17.26*	*1.00*	*9.90*
BEL_D	0.48	0.02	0.36	0.76	0.10	48.20	0.25	48.18
	0.50	*0.15*	*0.48*	*0.43*	*0.30*	*16.37*	*0.86*	*8.32*
BRAZIL	0.52	0.21	0.33	0.31	0.01	42.56	-1.44	42.44
	0.50	*0.40*	*0.47*	*0.46*	*0.11*	*17.18*	*1.33*	*11.21*
CZ	0.53	0.20	0.40	0.92	0.05	48.28	0.06	48.23
	0.50	*0.40*	*0.49*	*0.28*	*0.22*	*13.71*	*0.95*	*6.91*
DENMARK	0.49	0.13	0.34	0.73	0.10	49.77	-0.21	49.68
	0.50	*0.33*	*0.47*	*0.44*	*0.30*	*15.95*	*0.95*	*7.55*
FINLAND	0.52	0.18	0.37	0.64	0.02	50.12	0.03	50.10
	0.50	*0.38*	*0.48*	*0.48*	*0.15*	*16.39*	*0.95*	*7.10*
FRANCE	0.51	0.07	0.33	0.64	0.19	48.33	0.15	48.15
	0.50	*0.25*	*0.47*	*0.48*	*0.39*	*16.89*	*0.91*	*8.85*
GERMANY	0.52	0.18	0.34	0.73	0.18	49.71	0.35	49.62
	0.50	*0.38*	*0.47*	*0.45*	*0.39*	*15.76*	*0.73*	*8.30*
GREECE	0.50	0.71	0.44	0.56	0.05	47.88	-0.38	47.87
	0.50	*0.45*	*0.50*	*0.50*	*0.22*	*17.99*	*1.10*	*9.34*
HUNGARY	0.48	0.12	0.38	0.82	0.03	49.13	0.05	49.08
	0.50	*0.32*	*0.49*	*0.39*	*0.16*	*15.80*	*0.93*	*9.21*
IRELAND	0.52	0.12	0.34	0.58	0.06	48.18	-0.16	48.16
	0.50	*0.33*	*0.47*	*0.49*	*0.23*	*15.21*	*1.05*	*6.24*
ITALY	0.52	0.13	0.40	0.53	0.02	46.82	0.19	46.78
	0.50	*0.33*	*0.49*	*0.50*	*0.15*	*16.00*	*0.82*	*8.43*
JAPAN	0.49	0.05	0.39	0.00	0.00	50.32	0.03	50.88
	0.50	*0.22*	*0.49*	*0.00*	*0.05*	*15.47*	*0.91*	*6.63*
LUXEMBOURG	0.49	0.04	0.34	0.37	0.40	44.27	0.31	44.35
	0.50	*0.21*	*0.48*	*0.48*	*0.49*	*16.30*	*0.90*	*7.16*
MEXICO	0.50	0.37	0.27	0.27	0.04	43.02	-0.68	42.92
	0.50	*0.48*	*0.45*	*0.45*	*0.19*	*16.99*	*1.28*	*10.62*
NETHERLANDS	0.50	0.11	0.34	0.43	0.13	51.46	0.34	51.39
	0.50	*0.31*	*0.47*	*0.50*	*0.34*	*16.30*	*0.76*	*7.27*
NZ	0.48	0.09	0.31	0.70	0.29	52.00	-0.06	52.00
	0.50	*0.29*	*0.46*	*0.46*	*0.46*	*16.91*	*1.07*	*7.54*
SPAIN	0.52	0.14	0.45	0.37	0.04	44.94	0.19	44.90
	0.50	*0.35*	*0.50*	*0.48*	*0.18*	*16.41*	*0.83*	*8.99*
SWEDEN	0.50	0.22	0.35	0.80	0.16	50.36	0.04	50.37
	0.50	*0.41*	*0.48*	*0.40*	*0.36*	*16.18*	*0.95*	*6.89*
SWITZERLAND	0.50	0.03	0.35	0.54	0.27	48.62	0.28	48.59
	0.50	*0.17*	*0.48*	*0.50*	*0.44*	*16.12*	*0.83*	*7.99*
UK	0.50	0.34	0.35	0.74	0.09	50.20	-0.05	50.10
	0.50	*0.47*	*0.48*	*0.44*	*0.29*	*16.07*	*1.00*	*7.90*
USA	0.52	0.04	0.32	0.77	0.19	51.10	-0.30	50.87
	0.50	*0.21*	*0.47*	*0.42*	*0.39*	*16.38*	*1.19*	*7.68*

N= number of students sampled by country

Source: PISA (2000)

Table 3 – Summary statistics: read (Mean. *Standard Deviation*)

Country	girl	lctmat	brthord	misced	fathim	hisei	hedres	phisei
AUSTRIA	0.50	0.10	0.35	0.65	0.13	48.93	0.25	48.90
	0.50	*0.30*	*0.48*	*0.48*	*0.33*	*13.99*	*0.80*	*7.08*
BEL_FR	0.51	0.23	0.31	0.64	0.28	50.07	0.10	50.02
	0.50	*0.42*	*0.46*	*0.48*	*0.45*	*16.99*	*0.97*	*9.25*
BEL_D	0.48	0.02	0.35	0.77	0.10	48.63	0.30	48.60
	0.50	*0.15*	*0.48*	*0.42*	*0.30*	*16.35*	*0.80*	*7.82*
BRAZIL	0.52	0.21	0.33	0.31	0.01	42.57	-1.45	42.42
	0.50	*0.41*	*0.47*	*0.46*	*0.11*	*17.09*	*1.34*	*10.29*
CZ	0.54	0.19	0.40	0.92	0.05	48.73	0.10	48.68
	0.50	*0.39*	*0.49*	*0.27*	*0.22*	*13.90*	*0.92*	*6.74*
DENMARK	0.50	0.12	0.35	0.73	0.10	49.72	-0.22	49.66
	0.50	*0.33*	*0.48*	*0.44*	*0.30*	*16.02*	*0.93*	*6.51*
FINLAND	0.52	0.18	0.37	0.65	0.03	50.04	0.01	50.09
	0.50	*0.39*	*0.48*	*0.48*	*0.16*	*16.23*	*0.96*	*6.43*
FRANCE	0.51	0.07	0.34	0.64	0.19	48.09	0.16	47.98
	0.50	*0.25*	*0.47*	*0.48*	*0.40*	*16.85*	*0.89*	*8.23*
GERMANY	0.51	0.17	0.35	0.73	0.18	49.60	0.37	49.52
	0.50	*0.38*	*0.48*	*0.44*	*0.39*	*15.53*	*0.72*	*7.71*
GREECE	0.49	0.71	0.43	0.55	0.05	47.33	-0.37	47.26
	0.50	*0.45*	*0.50*	*0.50*	*0.22*	*17.82*	*1.10*	*8.78*
HUNGARY	0.49	0.12	0.39	0.82	0.03	49.12	0.09	49.10
	0.50	*0.32*	*0.49*	*0.38*	*0.16*	*15.65*	*0.92*	*8.62*
IRELAND	0.52	0.12	0.34	0.57	0.06	48.46	-0.14	48.50
	0.50	*0.33*	*0.47*	*0.49*	*0.24*	*15.58*	*1.03*	*6.09*
ITALY	0.51	0.13	0.40	0.54	0.02	47.03	0.19	46.94
	0.50	*0.33*	*0.49*	*0.50*	*0.15*	*15.92*	*0.82*	*7.86*
JAPAN	0.50	0.05	0.39	0.00	0.00	50.52	0.03	51.14
	0.50	*0.22*	*0.49*	*0.00*	*0.06*	*15.70*	*0.91*	*7.41*
LUXEMBOURG	0.50	0.05	0.35	0.39	0.40	44.58	0.31	44.65
	0.50	*0.21*	*0.48*	*0.49*	*0.49*	*16.26*	*0.91*	*6.72*
MEXICO	0.50	0.37	0.27	0.26	0.04	42.79	-0.68	42.71
	0.50	*0.48*	*0.44*	*0.44*	*0.20*	*17.15*	*1.28*	*10.17*
NETHERLANDS	0.50	0.10	0.34	0.44	0.13	51.60	0.36	51.53
	0.50	*0.30*	*0.47*	*0.50*	*0.34*	*16.13*	*0.73*	*6.64*
NZ	0.49	0.09	0.32	0.70	0.29	51.86	-0.04	51.80
	0.50	*0.29*	*0.47*	*0.46*	*0.45*	*16.68*	*1.06*	*6.72*
SPAIN	0.51	0.14	0.45	0.37	0.04	44.97	0.20	44.94
	0.50	*0.35*	*0.50*	*0.48*	*0.19*	*16.37*	*0.84*	*8.70*
SWEDEN	0.49	0.22	0.36	0.80	0.16	50.64	0.04	50.61
	0.50	*0.41*	*0.48*	*0.40*	*0.36*	*16.13*	*0.96*	*6.23*
SWITZERLAND	0.50	0.03	0.35	0.53	0.27	48.75	0.29	48.79
	0.50	*0.18*	*0.48*	*0.50*	*0.44*	*16.13*	*0.82*	*7.20*
UK	0.50	0.33	0.34	0.75	0.10	50.15	-0.04	50.08
	0.50	*0.47*	*0.47*	*0.44*	*0.29*	*16.09*	*1.00*	*7.20*
USA	0.53	0.04	0.33	0.77	0.19	51.07	-0.32	50.85
	0.50	*0.21*	*0.47*	*0.42*	*0.40*	*16.45*	*1.21*	*7.14*

N= number of students sampled by country
Source: PISA (2000)

Table 4 – Summary statistics: science (Mean. *Standard Deviation*)

Country	girl	lctmat	brthord	misced	fathim	hisei	hedres	phisei
AUSTRIA	0.50	0.10	0.34	0.66	0.13	48.90	0.23	48.82
	0.50	*0.30*	*0.47*	*0.47*	*0.34*	*13.79*	*0.81*	*7.33*
BEL_FR	0.51	0.22	0.29	0.64	0.29	49.86	0.09	49.79
	0.50	*0.42*	*0.45*	*0.48*	*0.45*	*16.89*	*0.96*	*9.75*
BEL_D	0.47	0.02	0.34	0.77	0.11	48.45	0.28	48.44
	0.50	*0.15*	*0.47*	*0.42*	*0.31*	*16.41*	*0.82*	*8.47*
BRAZIL	0.53	0.21	0.34	0.31	0.01	42.79	-1.45	42.62
	0.50	*0.41*	*0.47*	*0.46*	*0.10*	*17.34*	*1.33*	*11.15*
CZ	0.53	0.19	0.40	0.91	0.05	48.57	0.07	48.53
	0.50	*0.39*	*0.49*	*0.28*	*0.21*	*13.99*	*0.93*	*7.50*
DENMARK	0.50	0.12	0.35	0.73	0.10	49.51	-0.21	49.43
	0.50	*0.33*	*0.48*	*0.44*	*0.29*	*16.09*	*0.91*	*7.21*
FINLAND	0.50	0.18	0.38	0.65	0.02	50.09	0.01	50.13
	0.50	*0.39*	*0.48*	*0.48*	*0.16*	*16.23*	*0.97*	*6.95*
FRANCE	0.51	0.06	0.34	0.64	0.19	48.24	0.16	48.20
	0.50	*0.24*	*0.47*	*0.48*	*0.39*	*17.02*	*0.89*	*8.74*
GERMANY	0.51	0.18	0.35	0.73	0.18	49.62	0.36	49.52
	0.50	*0.38*	*0.48*	*0.45*	*0.39*	*15.56*	*0.73*	*8.06*
GREECE	0.49	0.71	0.43	0.54	0.05	46.35	-0.37	46.38
	0.50	*0.45*	*0.50*	*0.50*	*0.22*	*17.51*	*1.10*	*8.99*
HUNGARY	0.49	0.12	0.38	0.82	0.03	48.76	0.06	48.74
	0.50	*0.32*	*0.49*	*0.39*	*0.16*	*15.44*	*0.94*	*9.10*
IRELAND	0.52	0.12	0.33	0.57	0.06	48.48	-0.15	48.54
	0.50	*0.32*	*0.47*	*0.50*	*0.25*	*15.68*	*1.03*	*6.68*
ITALY	0.52	0.13	0.41	0.54	0.02	47.29	0.20	47.18
	0.50	*0.33*	*0.49*	*0.50*	*0.15*	*16.08*	*0.83*	*8.22*
JAPAN	0.50	0.05	0.39	0.00	0.00	50.78	0.03	51.35
	0.50	*0.22*	*0.49*	*0.00*	*0.05*	*15.82*	*0.90*	*8.17*
LUXEMBOURG	0.51	0.05	0.34	0.40	0.39	44.82	0.31	45.22
	0.50	*0.21*	*0.47*	*0.49*	*0.49*	*16.21*	*0.90*	*6.52*
MEXICO	0.50	0.36	0.27	0.27	0.04	42.69	-0.67	42.68
	0.50	*0.48*	*0.45*	*0.44*	*0.20*	*17.28*	*1.28*	*10.73*
NETHERLANDS	0.50	0.11	0.34	0.45	0.13	51.28	0.35	51.13
	0.50	*0.31*	*0.47*	*0.50*	*0.33*	*16.32*	*0.74*	*7.55*
NZ	0.49	0.09	0.33	0.71	0.28	51.82	-0.05	51.71
	0.50	*0.29*	*0.47*	*0.46*	*0.45*	*16.70*	*1.06*	*7.43*
SPAIN	0.51	0.14	0.44	0.37	0.04	44.97	0.20	44.99
	0.50	*0.34*	*0.50*	*0.48*	*0.18*	*16.36*	*0.84*	*9.12*
SWEDEN	0.50	0.22	0.36	0.80	0.15	50.47	0.06	50.43
	0.50	*0.41*	*0.48*	*0.40*	*0.36*	*16.31*	*0.96*	*7.09*
SWITZERLAND	0.51	0.04	0.35	0.54	0.27	48.83	0.29	48.89
	0.50	*0.19*	*0.48*	*0.50*	*0.45*	*16.27*	*0.81*	*7.96*
UK	0.51	0.33	0.34	0.75	0.10	50.03	-0.05	49.98
	0.50	*0.47*	*0.47*	*0.43*	*0.30*	*16.06*	*1.00*	*7.55*
USA	0.52	0.04	0.33	0.77	0.20	50.92	-0.32	50.81
	0.50	*0.20*	*0.47*	*0.42*	*0.40*	*16.43*	*1.22*	*7.73*

N= number of students sampled by country
Source: PISA (2000)

Table 5: Gross and Net differences between private (PRIV) and public schools (PUB)

	Math			Reading			Science		
Country	**Gross difference**	**OLS**	**Propensity score**	**Gross difference**	**OLS**	**Propensity score**	**Gross difference**	**OLS**	**Propensity score**
AUSTRIA	0.18	-0.40**	-0.35**	0.35	-0.37**	-0.25**	0.15	-0.36**	-0.41**
BRAZIL	1.01	0.40**	0.39**	1.10	0.40**	0.46**	0.87	0.40**	0.29*
FRANCE	0.23	0.01	-0.03	0.20	-0.13**	-0.14	0.27	-0.05	0.03
GREECE	0.62	-0.04	-0.42	0.42	-0.43**	-0.33	0.46	-0.26*	-0.08
IRELAND	0.87	0.32**	0.41	0.91	0.13	0.18	0.89	0.31**	-0.60
ITALY	0.17	-0.17*	-0.17	0.30	-0.14**	-0.22**	0.39	0.09	0.12
JAPAN	-0.10	-0.09	-0.11	-0.13	-0.19**	-0.13	-0.14	-0.22**	-0.16
MEXICO	0.69	-0.14*	-0.06	0.83	-0.21**	-0.14	0.60	-0.11	-0.13
NZ	0.64	0.17	0.48**[u]	0.64	0.05	1.09**[u]	0.70	0.21*	0.44[u]
SPAIN	0.61	-0.02	-0.30	0.71	0.05	-0.04	0.57	-0.07	-0.11
SWITZERLAND	0.02	-0.77**	-0.56**	0.19	-0.61**	-0.51**	0.14	-0.48**	-0.58**
UK	0.98	0.22**	0.74**	0.92	0.14**	0.23	0.86	0.12	0.37
USA	0.48	0.09	-0.01	0.48	0.12	0.02	0.39	0.02	0.03

[u]: average standardised bias after matching >10%
* significant at 5%
** significant at 1%

Table 6: Gross and Net differences between private government-dependent (PRIVGD) and public schools (PUB)

	Math			Reading			Science		
Country	**Gross difference**	**OLS**	**Propensity score**	**Gross difference**	**OLS**	**Propensity score**	**Gross difference**	**OLS**	**Propensity score**
AUSTRIA	0.31	-0.48**	0.03	0.41	-0.46**	0.06	0.30	-0.38**	-0.12
BEL_FR	0.44	0.17**	0.23**	0.48	0.26**	0.37**	0.35	0.20**	0.32**
BEL_D	0.62	0.18**	0.07	0.68	0.26**	0.28**	0.59	0.13**	-0.10
CZ	-0.15	-0.13*	-0.33**	0.08	0.06	0.09	-0.04	-0.10	0.10
DENMARK	0.02	0.03	0.04	0.02	-0.05	-0.05	-0.01	-0.04	-0.04
FINLAND	0.11	0.05	0.21	0.10	0.05	0.11	0.06	0.05	0.16
FRANCE	-0.01	0.25**	0.26**	-0.06	0.02	0.24**	-0.08	0.03	0.09
GERMANY	0.49	-0.09	0.03	0.64	-0.04	-0.09	0.53	0.04	-0.03
HUNGARY	0.17	0.09	0.15	0.12	0.01	-0.14	0.18	0.05	0.05
IRELAND	0.26	0.42**	0.09	0.41	0.27**	0.13**	0.39	0.53**	0.24**
LUXEMBOURG	-0.40	-0.07	0.00	-0.08	0.06	-0.18	-0.15	0.15**	0.00[u]
NETHERLANDS	0.17	0.02	-0.07	0.15	0.07	-0.02	0.08	-0.01	0.12
SPAIN	0.31	0.08**	0.07	0.35	0.14**	0.04	0.32	0.02	0.05
SWEDEN	-0.07	-0.16	-0.24	0.16	0.06	0.13	-0.09	-0.12	-0.19
SWITZERLAND	0.24	-0.67**	0.31	0.35	-0.55**	-0.11	0.31	-0.36**	0.17

[u]: average standardised bias after matching >10%
* significant at 5%
** significant at 1%

Table 7: Balancing of covariates: average (absolute) standardised bias before and after propensity score matching : private (PRIV) and public schools (PUB)

Country	topic	Average Bias Before Matching	Average Bias After matching	Average Bias Before Matching	Average Bias After matching
AUSTRIA	math	24.15	-2.78	35.82	9.42
	read	24.46	2.20	38.56	5.68
	scie	15.92	-0.54	33.64	3.66
BRAZIL	math	59.70	-0.73	81.14	4.70
	read	61.71	-0.06	81.64	7.10
	scie	60.55	3.27	81.37	5.99
FRANCE	math	10.41	-1.61	19.37	6.52
	read	13.06	6.60	21.33	10.63
	scie	13.53	-1.17	21.28	6.71
GREECE	math	21.57	9.16	57.99	30.90
	read	23.16	9.65	58.66	33.59
	scie	27.13	-4.83	58.86	46.44
IRELAND	math	63.09	-7.78	78.51	21.29
	read	69.25	6.91	82.16	29.56
	scie	69.10	-6.13	81.92	65.22
ITALY	math	20.36	-7.63	37.26	7.63
	read	15.59	-3.88	33.76	5.22
	scie	10.73	0.62	34.16	6.71
JAPAN	math	1.79	0.66	19.57	2.33
	read	1.94	2.74	19.55	7.84
	scie	5.96	4.78	24.02	8.45
MEXICO	math	65.10	-0.27	78.82	11.08
	read	65.50	8.20	80.39	27.20
	scie	64.46	0.78	78.97	17.10
NZ	math	43.58	-3.94	55.83	5.39
	read	50.30	**40.17**	61.74	60.17
	scie	44.57	**12.54**	57.30	24.56
SPAIN	math	53.48	**15.78**	72.44	18.50
	read	51.94	1.13	72.14	12.78
	scie	51.84	-7.07	70.43	11.97
SWITZERLAND	math	51.77	-3.57	54.55	15.03
	read	48.67	7.75	49.96	11.74
	scie	44.40	-4.07	45.99	8.09
UK	math	50.82	-3.63	79.28	11.91
	read	49.97	-0.76	79.57	15.02
	scie	46.57	-0.49	77.11	11.39
USA	math	32.77	-3.92	40.57	7.02
	read	20.13	-1.27	28.79	6.44
	scie	25.09	-8.71	33.23	12.54

Note: this table reports for each country and each topic the average (absolute) standardised bias of the different covariates. For a given covariate/regressor. the standardised (absolute) difference after matching is defined **as the (absolute value of the) difference of the sample means in the treated and matched comparison sub-samples as a percentage of the square root of the average of the sample variances in the treated and comparison groups** (cf. Rosenbaum & Rubin. 1985).
source: PISA (2000)

Table 8: Balancing of covariates: average (absolute) standardised bias before and after propensity score matching : private government-dependent (PRIVGB) and public schools (PUB)

Country	topic	Average Bias Before Matching	Average Bias After matching	Average Bias Before Matching	Average Bias After matching
AUSTRIA	math	28.97	4.60	29.24	5.71
	read	27.51	-0.02	27.51	4.37
	scie	28.75	0.55	28.75	4.20
BEL_FR	math	18.95	4.15	23.09	13.16
	read	16.82	1.38	20.48	7.75
	scie	10.88	1.90	15.36	13.26
BEL_D	math	18.21	-1.76	26.99	4.58
	read	15.36	0.72	23.38	11.44
	scie	19.55	-1.20	26.34	23.65
CZ	math	-2.48	-4.30	14.74	10.59
	read	-4.16	1.60	14.15	3.80
	scie	2.49	3.02	13.85	6.55
DENMARK	math	0.12	-0.03	10.24	2.21
	read	2.67	-1.81	12.55	3.65
	scie	4.10	0.98	13.98	4.62
FINLAND	math	15.78	-0.25	27.62	6.38
	read	11.78	2.80	22.75	6.75
	scie	11.14	9.92	24.33	11.88
FRANCE	math	-5.87	-0.08	17.53	3.71
	read	-4.52	-1.09	15.23	2.28
	scie	-2.67	-1.63	15.12	4.17
GERMANY	math	30.15	2.02	43.95	9.07
	read	28.79	1.47	39.74	6.30
	scie	29.58	-4.52	38.59	9.01
HUNGARY	math	0.21	-1.77	11.55	7.61
	read	3.19	-4.02	13.34	5.52
	scie	2.73	4.37	13.17	16.47
IRELAND	math	20.74	-6.19	21.49	13.09
	read	22.72	-6.49	23.01	8.84
	scie	22.99	-0.25	23.88	10.15
LUXEMBOURG	math	3.78	1.18	41.18	15.72
	read	2.10	-2.14	40.27	4.44
	scie	-3.81	**-10.13**	46.27	16.67
NETHERLAND	math	4.50	-3.48	14.80	7.20
	read	1.82	-0.50	12.65	3.85
	scie	1.89	3.14	13.41	3.73
SPAIN	math	8.60	0.86	19.57	5.62
	read	10.56	-0.46	20.72	2.79
	scie	10.94	-0.04	20.43	3.87
SWEDEN	math	21.32	-7.65	23.13	10.30
	read	25.17	-0.67	28.52	4.63
	scie	22.51	5.82	30.53	7.91
SWITZERLAND	math	17.25	5.37	20.41	13.35
	read	18.68	-2.75	22.37	4.24
	scie	11.20	-3.81	19.47	13.82

Note: this table reports for each country and each topic the average (absolute) standardised bias of the different covariates. For a given covariate/regressor. the standardised (absolute) difference after matching is defined **as the (absolute value of the) difference of the sample means in the treated and matched comparison sub-samples as a percentage of the square root of the average of the sample variances in the treated and comparison groups** (cf. Rosenbaum & Rubin. 1985).
source: PISA (2000)

Table 9 - Net difference between private, private government-dependent and public school achievement: recap for propensity score matching estimates

Country	Type of private school	Math	Reading	Science	*Average*
NZ	PRIV	0.48**[u]	1.09**[u]	0.44[u]	*0,67*
UK	PRIV	0.74**	0.23	0.37	*0,45*
BRAZIL	PRIV	0.39**	0.46**	0.29*	*0,38*
BEL_FR	PRIVGD	0.23**	0.37**	0.32**	*0,31*
FRANCE	PRIVGD	0.26**	0.24**	0.09	*0,20*
FINLAND	PRIVGD	0.21	0.11	0.16	*0,16*
IRELAND	PRIVGD	0.09	0.13**	0.24**	*0,15*
SWITZERLAND	PRIVGD	0.31	-0.11	0.17	*0,12*
BEL_D	PRIVGD	0.07	0.28**	-0.10	*0,09*
SPAIN	PRIVGD	0.07	0.04	0.05	*0,05*
HUNGARY	PRIVGD	0.15	-0.14	0.05	*0,02*
USA	PRIV	-0.01	0.02	0.03	*0,01*
NETHERLANDS	PRIVGD	-0.07	-0.02	0.12	*0,01*
IRELAND	PRIV	0.41	0.18	-0.60	*0,00*
AUSTRIA	PRIVGD	0.03	0.06	-0.12	*-0,01*
DENMARK	PRIVGD	0.04	-0.05	-0.04	*-0,02*
GERMANY	PRIVGD	0.03	-0.09	-0.03	*-0,03*
FRANCE	PRIV	-0.03	-0.14	0.03	*-0,05*
CZ	PRIVGD	-0.33**	0.09	0.10	*-0,05*
LUXEMBOURG	PRIVGD	0.00	-0.18	0.00[u]	*-0,06*
ITALY	PRIV	-0.17	-0.22**	0.12	*-0,09*
SWEDEN	PRIVGD	-0.24	0.13	-0.19	*-0,10*
MEXICO	PRIV	-0.06	-0.14	-0.13	*-0,11*
JAPAN	PRIV	-0.11	-0.13	-0.16	*-0,14*
SPAIN	PRIV	-0.30	-0.04	-0.11	*-0,15*
GREECE	PRIV	-0.42	-0.33	-0.08	*-0,28*
AUSTRIA	PRIV	-0.35**	-0.25**	-0.41**	*-0,33*
SWITZERLAND	PRIV	-0.56**	-0.51**	-0.58**	*-0,55*

[u]: average standardised bias after matching >10%
* significant at 5%
** significant at 1%
source: PISA (2000)