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The efficiency of public and publicly subsidized high schools in Spain: Evidence from PISA-2006

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This paper compares the efficiency of Spanish public and publicly subsidized private high schools by data envelopment analysis (DEA), employing the results provided by a hierarchical linear model (HLM) applied to PISA-2006 (Programme for International Students Assessment) microdata. The study places special emphasis on the estimation of the determinants of school outcomes. The educational production function is estimated through an HLM that takes into account the nested nature of PISA data. Inefficiencies are then measured through DEA and decomposed into two types: managerial (related to individual performance), and programme (related to structural differences between management models), following the approach adopted by Silva Portela and Thanassoulis. Once differences in students' backgrounds, school resources and individual management inefficiencies are removed, the results reveal that Spanish public high schools are more efficient than their publicly subsidized private equivalents.

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1. Introduction

The Spanish compulsory educational system is mixed or dual, a predominantly public network with a substantial private sector (67% of students go to public schools, 26% go to publicly subsidized private schools and 7% go to private-independent schools). Publicly subsidized private schools (hereafter PSPS) are owned and run privately, yet financed by local education authorities and the central government through a system of agreements regulated by the 1985 Right to Education Act (LODE, in its Spanish initials). The Spanish policy of financing certain private schools is aimed at allowing parents to choose freely between different schools and, indirectly, at stimulating inter-school competition to attract and retain students, which should generate improved school efficiency.

The administrative model of the Spanish PSPS system establishes the reciprocal rights and obligations of the owner of the private centre and the Education Authority with regard to the financial conditions, duration, extension and termination of the agreement and other conditions for the provision of education. PSPS' obligations include the following: to provide free teaching at the agreed educational level, to request authorization for the charging of any fees for complementary activities, to maintain a specific pupil/teacher ratio and to apply the same admission criteria as public schools (hereafter PS). In exchange, the Administration undertakes to finance the activity of the school, through a system of economic modules per educational establishment, as established in the General State Budget.

Formally, the Spanish PSPS system may be seen as a singular mechanism of public intervention in the education sector, combining the public funding and the private management of schools. These peculiar characteristics of PSPS invite the comparison of their efficiency compared to that of PS, yet Mancebón and Muñiz (2008) and Perelman and Santín (2011) are among the few to study this issue.

The scarcity of research in Spain into the impact of these two alternative systems of free educational provision (public and publicly subsidized) upon student performance justifies such a politically interesting analysis. Is the private management model of Spanish PSPS more efficient than the public management model of Spanish PS? Ultimately, this is the question the present study tackles, employing the data provided by the third wave of the Programme for International Student Assessment (PISA-2006), implemented by the Organization for Economic Cooperation and Development (OECD).

An initial examination of the average scores for PISA-2006 outcomes could lead to the conclusion that PSPS are

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more efficient than PS, since their crude (uncontrolled) results are higher. It is true that the average score for science competencies for PSPS is 502.86 and 475.08 for PS (the average score for the whole population being 488.40), while the t-test (5.89, p-value$=0.015$) indicates significant statistical differences between these two results.

However, focusing on output variables would only be fair if school resources were identical (Kirjavainen and Loikkanen, 1998), and in fact PS and PSPS differ as much in the inputs they employ as in their outputs. The principal differences are concentrated in pupil characteristics (socio-economic status, parents' educational level and employment, and immigration status), as Table A1 shows. Since several studies have proven that these characteristics affect students' academic results (Sirin, 2005), the challenge is to evaluate the performance of schools in a multi-dimensional setting.

In order to assess the impact of ownership upon school efficiency, we apply a non-parametric frontier analysis to the sample of Spanish PSPS and PS participating in PISA-2006. The theoretical framework is provided by research dedicated to assessing the net differential quality of public and private schools. The seminal work by Coleman *et al* (1982) is commonly considered as the origin of this literature; it concluded that private schools were more effective than public schools at educating students, even after controlling for differences in the personal and socio-economic background of students.

Since then a number of studies have attempted to test this result in a wide range of educational contexts, through the use of parametric and non-parametric techniques. The conclusions have been mixed: while some research tends to confirm the results obtained by Coleman *et al* (1982) (Hanushek, 1986; Chubb and Moe, 1990; Jiménez *et al*, 1991; Neal, 1997; Bedi and Garg, 2000; Stevans and Sessions, 2000; Mizzala *et al*, 2002; Bettinger, 2005; Opdenakker and Van Damme, 2006), in others the presumed superiority of private schools vanishes when the analysis includes a wide range of controls (Goldhaber, 1996; Sander, 1996; Kirjavainen and Loikkanen, 1998; Fertig, 2003; Abburrà, 2005; Calero and Escardíbul, 2007; Mancebón and Muñiz, 2008; Perelman and Santín, 2011) or is reduced to specific measurements of the output analysed (Greene and Kang, 2004), or to specific groups of students defined by race, ethnic group, or academic or socio-economic profile (Figlio and Stone, 1997).

In some cases, the effect is different for independent private schools and for PSPS (Corten and Dronkers, 2006; Dronkers and Robert, 2008). Most such studies concern the American educational system and adopt a parametric approach. This explains why further research using different case studies and methodologies is needed, as Cherchye *et al* (2010) point out. The present study may be seen as a new contribution to the puzzling debate on the relative efficiency of public and private schools, in the context of the Spanish educational system and using a non-parametric approach.

The empirical methodologies used here are hierarchical linear modelling (hereafter HLM) and data envelopment analysis (hereafter DEA). As far as we are aware, only one recent paper has employed these two methodologies jointly to measure pupil and school attainment (see De Witte *et al*, 2010). However, that study evaluates HLM and a variant of the DEA methodology (the Free Disposal Hull) as alternative techniques of performance estimation, concluding that parametric and non-parametric models can be used jointly to analyse school and pupil performance.

The present paper employs DEA and HLM sequentially. HLM allows the underlying educational technology in the PISA-2006 data to be estimated. The results from this part of the study are used to select the variables included in the subsequent DEA efficiency analysis. Thus, DEA and multilevel analysis are used as complementary but not alternative analytical tools. In our opinion, parametric techniques, such as HLM have major drawbacks as instruments for assessing school efficiency. First, they require assumptions regarding the statistical distribution of the error term. Second, the efficiency scores are dependent on the arbitrary functional form imposed on the data. Third, the single optimization process they use to estimate the coefficients assumes that the estimated function is applicable to each school evaluated. Last, parametric methods experience difficulties in dealing simultaneously with multiple outputs.

These characteristics of parametric methods do not adapt very well to the idiosyncratic nature of the education process (see Mancebón and Bandrés, 1999). For all these reasons, multilevel analysis is preferred as the feed of the selection of variables step in the DEA and this later as the efficiency evaluation tool. Additionally, using DEA the efficiency of an individual school can be decomposed into distinct components. Some of these are structural (programme efficiency in the present study) and others more susceptible of correction (management inefficiency), which may be very useful managerial information for schools.

The estimation of the underlying educational technology in the PISA-2006 data by means of HLM and the decomposition of the overall inefficiencies of each school into a managerial and a programme component are two aspects which distinguish the present study from previous research. Managerial efficiency results from schools' individual performance and programme efficiency results from the structural differences between public and private management models. For this decomposition, the approach of Silva Portela and Thanassoulis (2001), itself based on Charnes *et al* (1981), is applied.

The rest of the paper is organized as follows. Section 2 presents the estimation of the determinants of educational outcomes in PISA-2006. Section 3 empirically assesses the efficiency of Spanish PS and PSPS, and the final section offers the principal conclusions.

2. Estimation of the determinants of academic achievement in PISA-2006

This section describes the first and necessary step for the correct selection of the input variables needed to feed the DEA analysis performed in Section 3. Subsection 2.1 presents the literature review of the determinants of academic achievement. An econometric model is designed on the basis of this prior review, and the results are presented in Subsection 2.3, following a description in Subsection 2.2 of the data and methodology.

2.1. Educational outcome determinants: literature review

Our approach to the determinants of educational outcomes distinguishes between two levels, the first corresponding to student variables and the second to school variables. At the student level, we differentiate between three areas: first, personal variables; second, variables related to the socio-cultural and economic characteristics of the family; third, variables related to household resources and their use. At the school level, we establish four different areas: first, general variables describing the school; second, variables describing the school's students (and therefore the peer-effects generated by the interaction between students); third, variables related to the human and physical resources used by the school; fourth, variables to describe certain educational processes the school undertakes. On this basis, the present subsection reviews the effect of these variables upon educational outcomes, taking into account recent theoretical developments and the empirical literature.

At the student level, gender is among the most important personal variables. Girls' school performance is usually better than boys', although in the case of math and science competencies the opposite is true. In the three competencies measured in the PISA evaluation, for example, girls do better than boys only at reading, and lag behind in math and science (see OECD, 2006).

Still at the student level, considerable empirical evidence has shown that household socio-cultural and socio-economic characteristics are strong determinants of educational outcomes. The immigration status of the family has received special attention in recent years. Empirical evidence indicates that students born abroad tend to underperform (even after controlling for other significant variables), while there are no significant differences between national students and students born in the country to foreign parents (see Rong and Grant, 1992; Kao and Tienda, 1995; Chiswick and Debburman, 2004; Calero and Escardíbul, 2007).

Schnepf (2008), using TIMSS, PIRLS and PISA data for a set of eight OECD countries, shows that in general there is great heterogeneity within the group of immigrant students, the dispersion of their educational outcomes being higher than that of national students. Other socio-cultural and socio-economic characteristics, such as parental educational level and socio-professional category, have also received much attention. Some of the most relevant studies exploring these effects are Rumberger and Larson (1998), Gamoran (2001), Marks (2005) and Dronkers (2008).

The final set of variables at the student level concerns household resources and how students use them (see Wößmann, 2003; Calero and Escardíbul, 2007; Kang, 2007). Research undertaken with PISA data has stressed the incidence on student outcome of the availability of books and the use of computers with educational objectives within the household. Specifically, the availability of books is a very strong determinant of student performance, since it represents the family's cultural capital.

At the school level, general school characteristics are the first area of determinants to be addressed here. One of the most relevant factors, from both a theoretical and empirical point of view, is the nature of ownership (public or private). Evidence in this area is far from conclusive, as Section 1 shows.

Several variables describing the characteristics of school students are included in the second area of school level determinants. Such characteristics influence student performance through peer effects. Authors such as Coleman *et al* (1966), Farley (2006) and Willms (2006) have analysed the incidence of the socio-cultural and socio-economic profiles of peers upon student performance. Such an approach has also been used to analyse the peer effects generated by immigrant students. Calero and Escardíbul (2007) show, for example, how a high concentration of immigrant students is associated with negative effects on student performance. However, smaller concentrations of immigrant students do not generate any significant such effect.

Another area of determinants at school level is their physical and human resources. The detailed review offered by Hanushek (2003) makes clear that results in this area are far from conclusive. In the OECD (2007), where PISA data are used, most of the variables related to the availability and use of resources by the school are not statistically significant. Mancebón and Muñiz (2003), after reviewing 42 studies published between 1980 and 2002, suggest that a plausible explanation for the lack of significance of school resources in the explanation of student performance lies in the fact that most of the studies reviewed concern developed countries, with relatively high (and similar) levels of school resources.

Schools' educational processes are included in the fourth and final area of determinants at the school level. As an example of these processes we will refer solely to the grouping of students by ability level. Hanushek *et al* (2003) and Kang (2007) show that the negative effect of interaction with low-ability students is higher for this same group of low-ability students. Thus, student grouping by ability level leads to negative effects on low-performing students. The positive effect of grouping on high-performance students could then be expected to be cancelled out by the negative effect on low-performance students. This accounts for the results given by Gamoran (2004), who finds that these practices seldom produce the positive results expected.

2.2. Data and methodology

The present study uses PISA-2006 microdata for Spain. Since 2000, the PISA programme has examined every three years the academic achievement of 15-year-old students from different countries in three areas (reading, mathematics and science). In 2006, 57 countries (30 OECD and 27 non-OECD) took part in the PISA programme, which focused on the area of science. PISA results are synthesized using a scale with an average score of 500 and a standard deviation of 100, for each of the three competencies. This scale is divided into six levels of proficiency, level 1 corresponding to low-scorers and level 6 to those students who show high-level thinking and reasoning skills.

PISA designs its sample using a two-stage method. In the first stage, a sample of schools is randomly selected from the entire list of centres providing schooling for 15-year-olds. In the second stage, a random sample of 35 students is chosen from within each of the schools selected in the first stage. A school's probability of being selected by PISA is proportional to its size. Consequently, larger centres are more likely to be selected; nevertheless, students in larger schools have lower probabilities of being selected than students enrolled in smaller schools. Therefore, the probability of a school being chosen is equal to the result of multiplying the size of the centre (N_i) by the number of schools selected for the sample (n_c) and dividing by the total number of 15-year-old students (N).

$$p_i = \frac{N_i.n_c}{N} \tag{1}$$

The empirical analysis of the determinants of science competency scores in PISA-2006, which will be used as the main reference for the selection of variables for the DEA study, is based on HLM. This is due to the hierarchical structure of the PISA-2006 data set (see Bryk and Raudenbusch, 1988, who explain the convenience of applying multilevel models for analysing the effects of schools on educational outcomes).

The principle of the independence of variables among the students of each centre is not maintained, as a consequence of the above-mentioned two-stage sampling method. Students enrolled in the same school usually share socio-economic circumstances, making the average correlation among the variables of students within the centre higher than that of students from different schools (Hox, 1995). The intra-class correlation in the scientific competencies for the sample used in this paper from a null model is 0.15. The intra-class correlation is the proportion of the total variance explained by the differences between schools. If the intra-class correlation were equal to zero, it would not be necessary to use a multi-level model (as the entire variance would be explained by the differences in within-school characteristics).

HLM takes into account the nested structure of students in schools. HLM calculates a separate regression for each of the centres included in the sample (OECD, 2009a). Willms (2006) or Somers *et al* (2004) are examples of the application of this methodology in the educational field.

The present paper structures data into two levels: students (level 1) and centres (level 2). HLM allows the simultaneous analysis of variables of different levels and the study of their influence on inequality within and between centres. In other words, HLM permits the identification of the proportion of the total variance in scholastic achievement attributable to the characteristics of schools and students.

$$Y_{ij} = \beta_{0j} + \sum_{k=1}^{n} \beta_{1j} X_{kij} + \varepsilon_{ij}, \quad \varepsilon_{ij} \sim N(0, \sigma^2) \tag{2}$$

$$\beta_{0j} = \gamma_{00} + \sum_{1} \gamma_{01} Z_{lj} + \mu_{0j}, \quad \mu_{0j} \sim N(0, \tau_0) \tag{3}$$

$$\beta_{1j} = \gamma_{10} + \mu_{1j}, \quad \mu_{1j} \sim N(0, \tau_1) \tag{4}$$

$$\begin{aligned} Y_{ij} = \gamma_{00} + \sum_{k=1}^{n} \gamma_{10} X_{kij} + \sum_{1} \gamma_{01} Z_{lj} \\ + \sum_{k=1}^{n} \mu_{1j} X_{kij} + \mu_{0j} + \varepsilon_{ij} \end{aligned} \tag{5}$$

Y_{ij} is the expected science score of student i enrolled in school j. X_{kij} is a vector of k independent variables of the individual level and Z_j is a vector of l variables of the school level. Equation (5) is obtained by substituting Equations (3) and (4) (level 2) for the β in Equation (2) (level 1). It is possible to distinguish in Equation (5) a set of fixed effects ($\gamma_{00} + \sum_{k=1}^{n} \gamma_{10} X_{kij} + \sum_1 \gamma_{01} Z_{lj}$) from a set of random effects ($\sum_{k=1}^{n} \mu_{1j} X_{kij} + \mu_{0j} + \varepsilon_{ij}$). The main objective of the HLM model is to estimate mean effects for the whole sample. Consequently, as effects are fixed at the

Table 1 Total population and sample size for Spain in PISA-2006

15-year-old population	439 415
Number of students	19 604
Weighted number of students	381 686
Number of schools	682

Source: Authors' elaboration, based on PISA-2006 data.

student level, the final equation is:

$$Y_{ij} = \gamma_{00} + \sum_{k=1}^{n} \gamma_{10} X_{kij} + \sum_{1} \gamma_{01} Z_{lj} + \mu_{0j} + \varepsilon_{ij} \quad (6)$$

The dependent variable is the science score for students enrolled in PS and PSPS. This score is calculated using plausible values (PV hereafter) for each student and a replication method which permits efficient estimations (OECD, 2009b). PV are random values calculated from the distribution of the results. In PISA, students only answer part of the items constituting each test. PISA estimates each student's score for each item, using the distribution of probabilities of the different PV that the student has for the items. This procedure makes it possible to work with more than one estimation of student results.

The PISA-2006 sample for Spain consists of 19 604 students, grouped into 682 centres (Table 1). The sample used here includes 18 283 students from 643 schools. A total of 61.8% are enrolled in PS (61.4% of total schools) and 39.2% in PSPS. Students enrolled in non-subsidized private schools are not considered in the analysis.

2.3. Results

Table 2 presents the results of the multilevel regression. The first column lists the independent variables introduced into the model, grouped into three blocks, individual, family or school (for more information about the independent variables, see Table A2). These variables have been included as a result of the theoretical approaches and empirical evidence described in Subsection 2.1.

The second column presents the effects of these variables on PISA scores, following the same structure presented in Subsection 2.1 (two levels, divided into different areas). Table 3 provides information on the proportion of the variance explained, for each level, by the variables included in the complete model, in comparison to the null model. Nearly 85% of the variance in scores can be attributed to differences in student characteristics within schools (ie an intra-class correlation of 0.15).

The results for the individual level variables are consistent with previous empirical evidence. It is also noteworthy that students born earlier in the year continue to display a comparative advantage. According to OECD (2006) data, women score lower than men in science. The strongest effects from among all the factors included in the model are linked to the grade repetition variables (REPMORE or REPONE). The negative signs of these effects suggest, on the one hand, that grade repetition policies are ineffective and, on the other, that it is difficult to determine whether repetition of an academic year directly causes low achievement or whether 'repeaters' have certain characteristics in common—not included in the model—that make them low scorers.

Household socio-economic and cultural characteristics prove to be very important in explaining student performance in science. The results associated with the immigrant origin of the family are clear: students born in Spain to Spanish parents obtain better results in the science test than first-generation immigrant students, although their scores compared to second-generation immigrants are not significant.

This may be evidence of a process of assimilating and integrating immigrant families, especially since first-generation immigrant students who have not completed at least the entire compulsory secondary education level in Spain (ESO) score lower than first-generation immigrants who have been living in Spain for a minimum of four years. Students whose parents are economically active and belong to qualified white-collar households achieve higher scores in PISA. The results also show a positive and significant relationship between the years of schooling of mothers and the educational outcomes of their children.

Other results interesting to note are related to the analysis of household educational resources and their use by students. Certain coefficients of the variables related to computer use show that correctly using educational resources (such as computers) has a stronger impact on students' educational outcomes than the simple fact of having educational resources available at home. Similarly, the number of books in the household is considered to be a suitable proxy for family cultural capital, as it displays a strong and positive effect on PISA outcomes.

Ceteris paribus, students in PS obtain better results in the PISA science test than those enrolled in PSPS. This result must be emphasized, as previous studies of this subject in Spain, such as Calero and Escardíbul (2007) and Mancebón and Muñiz (2008), found no significant differences in public and private school educational outcomes, after controlling by large sets of variables. Furthermore, in the bivariate analysis, the former score lower than the latter. This different outcome can be explained by the fact that these papers are focused on different competencies. Additionally, Calero and Escardíbul (2007) used a previous PISA wave and Mancebón and Muñiz (2008) employed a different database with data for 17-year-old students. Moreover, the former base their results on a parametric technique that does not allow programme efficiency to be disentangled from overall efficiency.

Table 2 Estimation of fixed effects with robust standard errors in the HLM

Area	*Variable*	*Coefficient*
	INTERCEPT	352.4*** (6.4)
Individual		
	AGE	8.9*** (2.7)
	GIRLS	−17.8*** (−10.1)
	REPMORE (student enrolled in 1st or 2nd year of compulsory secondary education).	−110.7*** (−27.6)
	REPONE (student enrolled in 3rd year of compulsory secondary education). *Ref: Student enrolled in 4th year of compulsory secondary education*	−65.8*** (−29.7)
Household 1. Socio-economic and cultural characteristics		
	SECGEN (born in Spain; immigrant parents)	8.2 (0.7)
	FIRST3 (born in a foreign country; in Spain for 3 years or less)	−38.0*** (−3.4)
	FIRST4 (born in a foreign country; in Spain for 4 or more years) *Ref: Born in Spain; Spanish parents*	−20.7** (−2.2)
	LANG2 (national student that speaks a non-national language at home)	−6.0 (−0.5)
	LANG3 (foreign student that speaks a national language at home)	7.7 (0.9)
	LANG4 (foreign student that speaks a non-national language at home) *Ref: National student that speaks a national language at home*	2.7 (0.2)
	ACTIVE (both parents are economically active)	13.1*** (5.8)
	NQWHITEC (white collar, low skilled father)	−7.2** (−2.5)
	QBLUEC (blue collar, high skilled father)	−5.4** (−2.0)
	NQBLUEC (blue collar, low skilled father) *Ref: White collar, high skilled father*	−8.5*** (−3.0)
	MOTSCHY(years of schooling of the mother)	0.8*** (2.9)
	FATSCHY (years of schooling of the father)	0.4 (1.2)
Household 2. Educational resources and their use		
	NCOMPUT (no computer at home)	−7.1 (−1.4)
	SPUSECOM (sporadic use of computers)	−6.3** (−2.5)
	NUSECOM (never uses a computer) *Ref: Frequent use of computers*	1.9 (−2.0)
	SPOWRITE (sporadic use of word processors)	7.7*** (3.2)
	NEVWRITE (never uses word processors) *Ref: Frequent use of word processors*	−16.0*** (−4.6)
	25BOOKS (0 to 25 books at home)	−42.2*** (−13.2)
	100BOOKS (26 to 100 books at home)	−21.0*** (−7.9)
	200BOOKS (101 to 200 books at home) *Ref: More than 200 books at home*	−9.1*** (−3.2)
School 1. School characteristics		
	PRIVPUBF (publicly subsidized private high school)	−15.2*** (−1.7)
	SCHSIZ (school size)	−0.0 (−0.1)

Table 2 *Continued*

Area	*Variable*	*Coefficient*
	CITYSIZ2 (school in a city with a population of 100 000 to 1 000 000 inhabitants)	5.8 (1.5)
	CITYSIZ3 (school in a city with a population higher than 1 000 000 inhabitants)	21.6***
	Ref: School in town with a population smaller than 100 000	(3.5)
	NOTHERSC (few schools in the neighbourhood -maximum, 2-)	0.1 (0.0)
School 2. Students characteristics		
	ORIMMIG1 (proportion of immigrant students from 0.1 to 10%)	0.0 (0.0)
	ORIMMIG2 (proportion of immigrant students from 10 to 20%)	−9.9* (−1.7)
	ORIMMIG3 (proportion of immigrant students higher than 20%)	−17.7*** (−3.4)
	SCEDMO (average years of schooling of the mothers)	2.9** (2.6)
	PCGIRLS (proportion of girls at school)	44.4** (2.0)
	SCNQWHIT (white collar, low skilled parents -mode-)	−6.4 (−1.0)
	SCQBLUE (blue collar, high skilled parents -mode-)	3.5 (0.8)
	SCNQBLUE (blue collar, low skilled parents -mode-)	−3.2
	Ref: White collar, skilled parents -mode-	(−0.6)
School 3. School resources		
	STRATIO (student-teacher ratio)	0.3 (0.6)
	PTEACH (proportion of part-time teachers)	0.1 (0.5)
	CLSIZ (class size)	−0.2* (−1.9)
	COMPWEB (proportion of computers connected to the Internet)	−1.9 (−0.3)
	IRATCO (ratio of computers for instruction to school size)	−60.1*** (−2.9)
	NCOUNS (no school counsellors at the centre)	−0.3 (−0.1)
School 4. Educational practices		
	AUTOHIRE (school with autonomy in selecting teachers for hire)	−3.9 (−1.2)
	AUTBUDG (school with budgetary autonomy)	4.3 (1.1)
	AUTEXT (autonomy for selecting textbooks)	5.1 (0.8)
	AUTCONTE (school with autonomy for selecting course contents)	2.9 (0.4)
	AUTOCU (school autonomy for modifying the curriculum)	−3.6 (−0.9)
	CRITADMI (religious or philosophical issues are used as an admittance criterion)	2.9 (0.7)
	STREB (ability grouping between classes)	−3.9 (−1.2)
	STREW (ability grouping within classes)	−1.1 (−0.3)
	Number of level units	18.283

***Statistically significant at the 0.01 level; **statistically significant at the 0.05 level; *statistically significant at the 0.10 level; *t*-ratio (in brackets). Estimations were computed using HLM 6.25.
Source: Authors' elaboration based on PISA-2006 data.

Table 3 Multilevel regression: random effects

Variances	*Null model*	*Complete model*
Schools (u_j)	1221.8	411.9
Students (ε_{ij})	6748.3	4117.3
Total ($u_j+\varepsilon_{ij}$)	7970.1	4529.2
% of total variance explained by variables		43.2
% of level 1 (students) variance explained by variables		39.0
% of level 2 (schools) variance explained by variables		66.3

Source: Authors' elaboration, based on PISA-2006 data.

The results of the present study show that peer effects are the most important variables at the school level. The results in Table 2 also show that the negative impact upon students' educational outcomes of sharing their class with immigrant students is only significant when this proportion exceeds a certain threshold. The educational level of mothers has a positive effect not only upon their children but also upon their children's classmates. Furthermore, the number of girls in a school appears to have a positive impact on PISA outcomes.

The only significant variables among the school resources factors included in the present analysis were class size and the instructional computers/school size ratio. Large class size appears to have a negative effect on educational outcomes. The strong and negative sign linked to the ratio of computers variable remains unexplained and should be the subject of further research (a negative correlation between the ratio of computers and the reading results for Switzerland in PISA-2000 was also found by Meunier, 2008). The lack of significance of variables such as the student/teacher ratio or the existence of school counsellors should help policymakers to evaluate the opportunity cost of common input-based policies.

Finally, no significant effects were found among the educational practices variables. Different types of school autonomy were shown to be irrelevant. However, deeper insight into this factor would require more detailed data on different aspects of autonomy. Consequently, the results in this area should be treated with caution. When interpreting the ability grouping variables, it must be remembered that, although non-significant *on average*, ability grouping policies may have important effects on different types of students, as Subsection 2.1 explains.

3. Public and publicly subsidized private high schools in Spain: an efficiency assessment from PISA-2006 data

In this section, an efficiency analysis using the DEA methodology is used to compare the efficiency of the Spanish public and publicly subsidized private high schools participating in PISA-2006. The sample of schools finally evaluated, following the suppression of missing values, comprises 567 schools, 222 of them PSPS and 345 PS. The analysis compares the academic results obtained by pupils in each school with all the inputs relevant to the obtaining of those results. A school is considered efficient if no other in the sample achieves better outcomes with equal or fewer resources. Conversely, an inefficient school obtains results inferior to those potentially achievable from its inputs.

The three stages required by any productive efficiency analysis are now described in turn: the selection of inputs and outputs, the choice of the evaluation model and the discussion of the results.

3.1. The selection of Spanish high school inputs and outputs for DEA analysis

The first step in a productive efficiency analysis is to select the variables to proxy the outputs and inputs of evaluated decision-making units (DMUs). The PISA-2006 data are plentiful concerning student competence in different subjects (mathematics, reading and science), their socio-economic and family background and school resources.

The prescriptions generally accepted in the DEA literature on variable selection establish certain minimum requirements (Bessent and Bessent, 1980): a conceptual basis for the relationship of inputs to outputs; an empirically inferred relationship of measured inputs to outputs; an association between increases in inputs and increases in outputs; and measurements without zero elements.

To comply with all these conditions, variable selection is based on the results obtained from the empirical research into the determinants of educational outcomes in PISA-2006 carried out in Section 2. Using this procedure, evidence from previous literature is combined with evidence from the present sample (the HLM model). We think that the selection of variables based exclusively on earlier literature concerning the determinants of educational outcomes is insufficient, due to the lack of consensus on the effects of certain variables in heterogeneous empirical studies (applied to different countries, different level of aggregation, different data bases, etc). Taking this into account, it is considered more convenient to empirically contrast the relationship between output and inputs in each specific research context, to make the DEA analysis more reliable, since the correct selection of inputs is critical in DEA.

For this reason, we decided to combine evidence from previous literature with evidence from our own sample (the HLM model). The conclusions extracted from the HLM regressions permit the variables for the subsequent DEA efficiency analysis to be selected in a robust empirical fashion. Consequently, the scores of 15-year-old students in science competencies are selected as the output of Spanish PS and PSPS, and all the statistically significant variables in the HLM performed in the previous section are the inputs.

To summarize, the efficiency of the Spanish PS and PSPS participating in PISA-2006 is estimated on the basis of 12 variables. One of these proxies output (PV), two approximate the resources available to each school (IRATCO and CLSIZ) and the remaining nine proxy students' socio-economic and cultural background. This specification is given the name of model 1. The number of schools evaluated (567) permits the introduction of numerous variables in the efficiency analysis, and in this sense the relationship between the number of DMUs and the number of variables complies with all the 'rules of thumb' suggested in the relevant DEA literature (see Banker *et al*, 1989; Golany and Roll, 1989; Boussofiane *et al*, 1991 or Dyson *et al*, 2001). Table 4 summarizes the maximum, minimum, average and standard deviation for all these variables.

3.2. The DEA model employed

In addition to choosing input variables, efficiency analysis requires deciding how to measure performance. In recent years, during which the assessment of the efficiency of different samples of educational institutions has expanded notably, it has become clear that parametric techniques have major drawbacks as instruments for assessing the results of academic institutions.

By contrast, non-parametric frontier methods, such as DEA, have shown themselves to be much more attractive in this context. The advantages claimed for this methodology in the assessment of school efficiency have been reinforced by its intensive use (Worthington, 2001). The basic approach of DEA is to view schools as productive units which use multiple inputs (controllable and non-controllable) and outputs. The method produces measurements of school efficiency by deriving a frontier production function (efficiency frontier) and measuring the distance of observations to this frontier. Observations on the frontier obtain an efficiency score of 1, while those under it obtain scores below 1, depending on their location.

This technique, based on mathematical programming, has evolved considerably since it first appeared in the seminal paper of Charnes *et al* (1978). Specifically, multiple extensions of the initial model have attempted to adapt the mathematical formulation and the process of obtaining efficiency indices to the peculiarities of the particular sector analysed, to the nature of the variables constituting the analysis, or to the aims of the research in question (see Thanassoulis, 2001; Cooper *et al*, 2004a, b).

From among the different proposals offered by the literature, the approach adopted by Silva Portela and Thanassoulis (2001), based on Charnes *et al* (1981), is of particular interest for the task at hand. This methodology

Table 4 Variables used in the DEA model

Variable	*Definition*	*PSPS*				*PS*				*Total*			
		Min.	*Max.*	*Mean*	*SD*	*Min.*	*Max.*	*Mean*	*SD*	*Min.*	*Max.*	*Mean*	*SD*
Output: PV	Outcome in science (plausible value)	364.9	600.5	502.9	85.69	268.7	588.0	475.1	90.07	268.7	604.6	488.1	90.60
Input 1: NATIONAL	Percentage of students born in Spain	25.0%	100%	95.2%	0.76	17.5%	100%	90.04%	0.96	17.5%	100%	91.88%	0.68
Input 2: PCGIRLS	Proportion of girls at school	0.0%	79%	52.1%	2.01	10.5%	74%	48.64%	0.68	0.0%	100%	49.46%	0.72
Input 3: NOREPET	Percentage of students not repeating any grade	19.3%	100%	72.4%	1.26	6.8%	100%	51.19%	1.07	6.8%	100%	59.84%	0.85
Input 4: MOTSCY	Mother's years of schooling	5.1	15.3	10.4	4.43	5.1	15.3	8.8	4.67	5.1	15.7	9.6	4.73
Input 5: REGWRITE & SPOWRITE	Percentage of students who use the computer frequently or occasionally to write documents	48.1%	100%	89.6%	0.77	25.0%	100%	84.51%	0.87	25.0%	100%	86.82%	0.60
Input 6: QWHITEC	Percentage of students whose father's job is white collar high skilled	5.0%	94%	38.2%	2.07	2.8%	76%	22.30%	1.10	2.8%	97%	30.69%	1.00
Input 7: LANG1	Percentage of native students who speak national language at home	25.0%	100%	93.3%	0.79	17.5%	100%	87.19%	1.05	17.5%	100%	89.16%	0.75
Input 8: 500BOOKS	Percentage of students with over 200 books at home	3.2%	77%	28.3%	1.48	2.7%	61%	17.99%	0.86	2.7%	85%	23.95%	0.86
Input 9: ACTIVE	Percentage of students whose father and mother are both in active working population	33.0%	100%	73.8%	1.24	23.6%	100%	65.12%	1.02	23.6%	100%	68.98%	0.76
Input10: IRATCO	Ratio of computers for instruction to school size*	0.01	0.71	0.06	0.04	0.02	0.56	0.12	0.10	0.01	0.71	0.10	0.09
Input 11: CLSIZE	Average class size*	13	53	30.4	10.91	13	53	26.3	8.33	13	53	27.8	9.67

*Variables were redefined in such a way that their relationship with output was positive according to the HLM results, a basic requirement of DEA models for the estimation of efficiency. For this reason IRATCO and CLSIZE have been introduced in the DEA model in their reverse value.
Source: Authors' elaboration, based on PISA-2006 data.

decomposes the overall measurement of efficiency, computed using DEA, into managerial and programme components. The consequent attraction is that it permits differentiation between inefficiencies attributable to the individual management of a decision-making unit (hereafter DMU) and those attributable to a unit's management programme. This property is of great interest, since the aim of the present study is to compare the behaviour of schools, employing different management models. This approach is explained using Figure 1.

This represents an organization (Z) which plays its productive role according to a specific management model (model A). Its efficiency is evaluated compared to a set of organizations, of which some employ the same management model (model A) and the rest a different model (model B). The application of DEA to the two subsamples will identify the two frontiers observable in the figure.

The assessment of the output of organization Z in relation to all the schools in the sample (regardless of their specific management model), using DEA, will attribute an overall rate to this organization with a value of $Z'Z'''/Z'Z$ (maximum output in the sector/real output of Z). This ratio, since it is the result of comparison with all schools in the sector, includes those effects attributable to individual school management and those attributable to the structural differences between the two management programmes coexisting in the sample.

In order to determine what part of Z's efficiency is attributable to individual management (managerial efficiency), its production must be compared to that of the remaining schools having the same management model, namely model A. The value of the efficiency index which DEA will now attribute to Z will be $Z'Z''/Z'Z$ (maximum output in model A/real output of Z). This efficiency, since it is the result of comparison with organizations functioning under the same management model, is attributable only to individual school practices.

Finally, Z's programme efficiency will be the residual part of the overall efficiency not attributable to individual management. Graphically, this is determined by the index

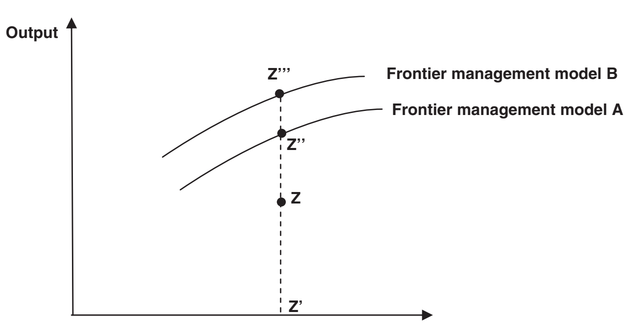

Figure 1 Efficiency decomposition according to Silva Portela and Thanassoulis (2001).

$Z'Z'''/Z'Z''$ (maximum output in the sector/output which Z would use, if its individual management were efficient). It can therefore immediately be confirmed that:

$$\text{Overall Efficiency} = (\text{Managerial Efficiency}) \times (\text{Programme Efficiency}) \tag{7}$$

From this relationship the different efficiency indices can be computed by resolving three DEA models (see Equation (8)): one for DMUs employing model A (the managerial efficiency of type A units); another for those guided by model B (the managerial efficiency of type B units); and a third for all schools (the overall efficiency of each organization). Programme efficiency is obtained using a simple quotient between overall and managerial efficiency.

$$\begin{aligned} &\text{Maximize: } \theta_0 \\ &\text{subject to: } \sum_{j=0}^{n} \lambda_j x_{ij} \leqslant x_{i0}, \qquad i = 1, 2, \ldots, m \\ &\sum_{j=0}^{n} \lambda_j y_j \geqslant \theta_0 y_0 \\ &\sum_{j=0}^{n} \lambda_j = 1 \\ &\lambda_j \geqslant 0 \end{aligned} \tag{8}$$

θ_0 is the efficiency score of school 0, x_{ij} is the input i of school j, y_j is the output of school j and λ_j are the Lambda values (the raw weights assigned to the peer units of each school; see Cooper *et al*, 2004a).

3.3. Results of the efficiency analysis

Table 5 presents the results from the efficiency analysis performed according to the previously established criteria. The efficiency estimations were computed using ON-FRONT software. The solved DEA models applied the variant of variable returns to scale assumption (Banker *et al*, 1984) and were oriented to maximizing output.

The 'variable returns to scale' (VRS) model does not assume full proportionality between the inputs and outputs incorporated in the mathematical programming model and it is based only on axioms of convexity and free availability. These characteristics are very important in our estimations because all the variables selected as inputs and outputs are ratios and have upper limits. In such cases, the VRS formulation of the DEA model should be used because if not perverse and technically incorrect results will be produced (see Hollingsworth and Smith, 2003). Furthermore, by incorporating the assumption of VRS, the DEA model links the estimation to a very flexible production function and supplies an estimation of the pure technical efficiency not contaminated by the scale of operation. This aspect is fundamental in the educational

Table 5 Efficiency scores of inefficient schools

	Mean efficiency			*t-test*		
	PSPS	*PS*	*Total*	*Dif. in means*	*Standard error*	*Test*
Managerial efficiency	0.930	0.926	0.928	0.004	0.009	0.478
Programme efficiency	0.962	0.982	0.964	−0.020	0.005	−3.996***
Overall efficiency	0.919	0.925	0.923	−0.006	0.008	−0.764
	(20.05)	(43.64)	(37.20)			

***Indicates statistically significant differences between PSPS and PS at a 1% significance level.
Figures in brackets are the percentage of schools with maximum efficiency (>0.99).

sector where neither conceptual nor empirical reasons may back up the increasing, constant or decreasing returns to scale assumption.

With regard to the output orientation formulation, it fits the characteristics of the problem analysed because of the uncontrolled base of the majority of inputs incorporated to the analysis. In this environment, the relevant efficiency comparisons take place among high schools generating the same or more outputs with the same or fewer inputs.

The first row of Table 5 shows the efficiency rates resulting exclusively from the individual performance of each school (managerial efficiency). The results of PS in this column cannot be compared to those of PSPS, since the reference frontier used in each case was different.

The second row displays the efficiency attributable to structural differences between the management models, public or private, employed by each school (programme efficiency). This value has the greatest interest for the aims of the present research.

Finally, the third row presents the estimations of overall efficiency, that is to say the comparison of all schools in the sample, independently of ownership type. Therefore, this value includes the effects of individual performance (managerial efficiency) and those of the managerial model employed in PS and PSPS (programme efficiency).

The results in Table 5 indicate that the difference between overall efficiency in PS and PSPS is very slight and statistically non-significant. In other words, once differences in student characteristics and school resources are taken into account, the advantages that PSPS display in crude educational results disappear. However, overall efficiency comprises the effects of both individual school performance and school management model, meaning that overall efficiency rates do not permit the correct interpretation of the crude results obtained here without first decomposing managerial and programme efficiency.

To resolve this question, let us consider the results provided in the second row in Table 5, the efficiency due to structural differences between management models (programme efficiency). Although overall efficiency values do not diverge greatly, the differences found in this case become statistically significant in favour of PS. That is to say, the removal of managerial inefficiencies results in the efficiency of the public management model exceeding that of the private model. Furthermore, the percentage of schools displaying maximum overall efficiency (values in brackets in Table 5) is considerably higher for PS than for PSPS, producing the conclusion that best practices are implemented by a higher proportion of PS than PSPS.

To explore into the differences between the inputs of PS and PSPS, a radar graph is built. As Figure 2 shows, the main differences between the inputs of PS and PSPS are due to the non-school variables (NOREPET, QWHITEC and 500BOOKS), all of these being higher in PSPS than in PS. This may explain the higher efficiency scores of PS: the higher crude outcomes of PSPS in science competencies in PISA 2006 are insufficient to outweigh their considerable advantages in terms of non controllable inputs.

Additionally, a sensitivity analysis and an outlier analysis were performed to test the robustness of the results. Such analyses are essential when using DEA, since it is a non-parametric technique.

Three alternative specifications to model 1 are proposed for the sensitivity analysis. First the variable CLSIZE (model 2) was removed, then the variable IRATCO (model 3) and, finally, education resources, CLSIZE and IRATCO (model 4). This procedure was adopted because the effects of these variables upon educational outcomes are unclear, to judge by earlier literature (Hanushek, 2003). Furthermore, the aim is to analyse whether the differences found in programme efficiencies between PS and PSPS are reduced when school resources are removed from DEA models.

Table 6 displays the programme efficiency scores for the four specifications described above. According to the *t*-test the results are robust in the four different models. The sensitivity test of the Spearman rank correlation coefficient, suggested by Hughes and Yaisawarng (2004) for enhancing the credibility of DEA results, also verifies the robustness of the results obtained in model 1. The correlation of the ranks for each pair of efficiency scores is very high and statistically significant (the rank correlation results are available from the authors on request). In conclusion, once differences in pupils background, school resources and individual management inefficiencies are removed, Spanish PS are more efficient than their PSPS counterparts.

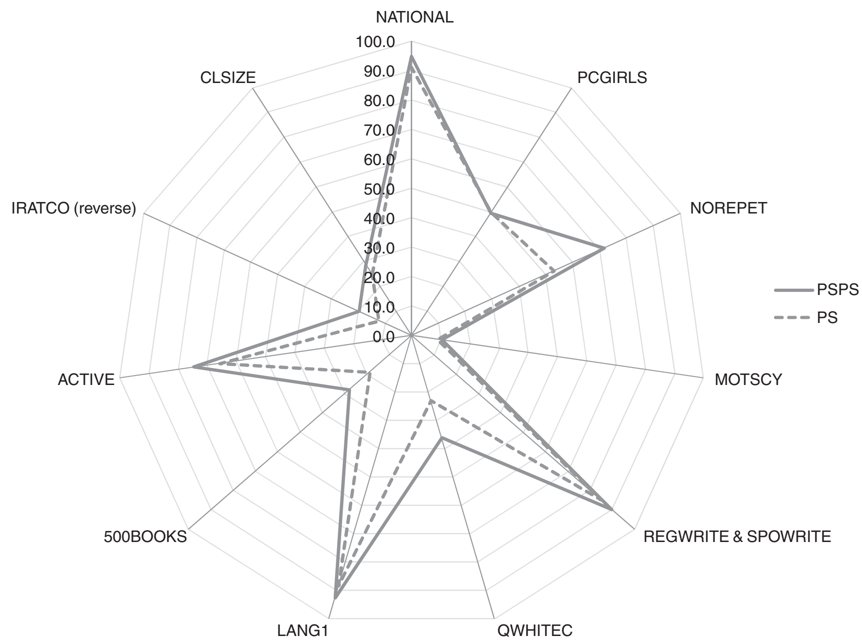

Figure 2 Input variables compared between PSPS and PS.

Table 6 Programme efficiency scores using alternative DEA models (inefficient schools)

	Mean efficiency			*t-test*		
	PSPS	*PS*	*Total*	*Dif. in means*	*Standard error*	*Test*
Model 1	0.962	0.982	0.964	−0.020	0.005	−3.99***
Model 2	0.960	0.988	0.965	−0.027	0.007	−4.01***
Model 3	0.963	0.981	0.966	−0.018	0.007	−2.64***
Model 4	0.964	0.987	0.969	−0.022	0.007	−3.41***

***indicates statistically significant differences between PSPS and PS at a 1% significance level.

Additionally, an outlier analysis was performed. Following standard statistical practice, outliers were defined as those DMUs for which at least one input variable is distant from the nearest quartile by over three times the interquantile range. These DMUs were removed from the sample and the entire efficiency analysis was repeated again. The results were practically identical to the results given in Table 5 and the conclusions are unchanged. The results of outlier analysis are available from the authors upon request. These findings support the robustness of the conclusion about the higher efficiency of Spanish PS *versus* PSPS.

4. Conclusions

The present paper performs a non-parametric efficiency analysis of Spanish PS and PSPS, using as reference the data supplied by PISA-2006. For the analysis to be rigorous, a detailed study of the determinants of students' educational outcomes is made, employing HLM. Given the absence of any generalized empirical consensus regarding the variables stimulating students' academic success, it is believed that any evaluation of school efficiency requires a thorough analysis of the empirical relationship between the variables selected as inputs and outputs.

The principal results obtained in this regard indicate the special importance of household socio-economic and cultural characteristics in explaining student performance in science competencies. Other variables of great influence upon educational results at the individual level are gender, grade repetition and household educational resources (such as books and computers) and their use by students. Nearly 85% of the variance in scores can be attributed to differences in student characteristics within schools.

At the school level, peer effects (the educational level of mothers, proportion of girls at school and proportion of immigrant students) are the most important variables in achieving good science competencies. The only significant variables among the school resources factors included in the present analysis were class size and the instructional computers/school size ratio.

These results, which confirm those of a number of previous studies, allowed the further development of the present efficiency analysis of PS and PSPS in Spain. The most important result is that PS are more efficient than PSPS; the higher scores achieved by PSPS in science competencies, as measured in PISA 2006, cease to exist when school resources, the student characteristics of each school and individual management inefficiencies are discounted. This conclusion is in line with other international studies, where private high schools are shown to be inefficient compared to their public counterparts (Kirjavainen and Loikkanen, 1998; Barbetta and Turati, 2003; Braun *et al*, 2006; Lubienski and Lubienski, 2006; Lubienski *et al*, 2009).

In the context of PISA data, the conclusions extracted from comparative efficiency analyses of public and private schools are mixed. While Calero and Waisgrais (2009) show that Spanish private (PSPS and private independent) schools exert a negative influence upon science competencies, as measured by PISA-2006, other papers employing PISA-2003 data for Spain indicate that neither PS nor PSPS are superior (Calero and Escardíbul, 2007; Perelman and Santín, 2011). The principal conclusion of the last-named authors is that once the effects related to the social composition of schools are discounted, the differences in educational performance become statistically non-significant. This invites the conclusion that these differences are more closely related to student type in each school and to the differential characteristics of each school than to school quality.

Since Calero and Escardíbul (2007) focus their analyses on the results from the mathematics assessment in PISA-2003, the explanation of divergences with regard to the present study and to that of Calero and Waisgrais (2009), using PISA-2006, is possibly to be found in a certain specialization of PS in science, a subject in which PSPS prove to be less efficient, according to the results obtained here. The empirical testing of this hypothesis is unfortunately far beyond the objectives of the present paper, but could be a specific issue for further research. Nevertheless, in the view of the present authors, it is unsurprising that PS appear to be more efficient than PSPS. In Finland, a benchmark for educational outcomes in every edition of PISA, almost all schools are public.

Another conclusion of the present paper to be underlined is that the superior efficiency of PS *versus* PSPS remains even when school resources are eliminated from the DEA analysis. This result emphasizes that school resources are less important than student characteristics with regard to school performance. This conclusion too confirms many previous studies of the determinants of educational outcomes (Hanushek, 2003).

Finally, it must be noted that the DEA results are robust to different specifications of the model, as the sensitivity analysis shows. In addition, the efficiency estimations are not sensitive to outliers or specialization patterns in any of the variables included in the DEA models.

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Appendix

Table A1 Student profiles in Spanish PS and PSPS

Type of variable	*Questionnaire item*	*PSPS*	*PS*	*Total*	*t-test dif. in means*
Results	Years repeated (REPMORE & REPONE)	1.20	1.18	1.18	0.94
Expectations—aspirations	Students' expected occupational status (BSMJ)	62.24	57.92	59.17	5.79***
Attitudes toward science	Plausible value in interest in science (PVINTR)	526.23	539.47	535.86	−3.51***
	Plausible value in support for scientific inquiry (PVSUPP)	530.53	526.94	527.92	0.77
	General interest in learning science (INTSCIE)	−0.17	−0.19	−0.19	0.64
	Enjoyment of science (JOYSCIE)	−0.11	−0.17	−0.15	1.87*
	Science self-efficacy (SCIEEFF)	−0.01	−0.13	−0.10	3.49***
	General value of science (GENSCIE)	0.34	0.26	0.28	2.65***
	Personal value of science (PERSCIE)	0.05	0.03	0.03	0.81
	Science activities (SCIEACT)	−0.14	−0.16	−0.15	0.76
Personal	Age (AGE)	15.83	15.82	15.82	0.36
Occupational status of parents	Mother's occupational status. SEI index (BMMJ)	41.22	36.07	37.59	4.34***
	Father's occupational status. SEI index (BFMJ)	44.56	38.15	39.93	7.00***
	Highest occupational status of parents. SEI index (HISEI)	47.82	41.11	42.96	6.85***
Educational level of parents	Mother's years of schooling (MOTSCY)	10.39	8.80	9.24	5.79***
	Father's years of schooling (FATSCY)	10.60	8.72	9.24	7.33***
	Maximum years of schooling of parents (PARESCY)	11.90	10.32	10.75	6.78***
Household possessions scale indices	Index of family wealth possessions (WEALTH)	−0.07	−0.23	−0.18	4.87***
	Index of cultural possessions at home (CULTPOSS)	0.19	0.00	0.05	5.30***
	Index of home educational resources (HEDRES)	0.32	0.17	0.21	4.51***
	Index of home possessions (HOMEPOS)	0.22	−0.02	0.04	6.74***
	Index of economic, social and cultural status (ESCS)	−0.08	−0.57	−0.44	7.30***

***, **and *indicate statistically significant mean differences between PSPS and PS at the 1, 5 and 10% significance level, respectively.
Name of the variable in the PISA database in brackets.
Source: Authors' elaboration based on PISA-2006 data.

Table A2 Variables employed in the HLM

	N	*Min.*	*Max.*	*Mean*	*Standard dev.*
Individual					
AGE (student's age, in years)	18 283	15.33	16.33	15.84	0.29
WOMEN (gender dummy: 1 if female)	18 283	0	1	0.50	0.50
REPMORE (1st-2nd year of ESO)	18 283	0	1	0.06	0.23
REPONE (3rd year of ESO)	18 283	0	1	0.26	0.44
NOREPET (4rd year of ESO)	18 283	0	1	0.68	0.47
Household 1. Socio-economic and cultural characteristics					
NATIONAL (born in Spain; Spanish parents)	18 283	0	1	0.95	0.21
SECGEN (born in Spain; immigrant parents)	18 283	0	1	0.01	0.07
FIRST3 (born abroad; in Spain for 3 or less years)	18 283	0	1	0.02	0.12
FIRST4 (born abroad; in Spain for 4 or more years)	18 283	0	1	0.03	0.16
LANG1 (national; national language at home)	18 283	0	1	0.94	0.23
LANG2 (national; non-national language at home)	18 283	0	1	0.01	0.08
LANG3 (foreign; national language at home)	18 283	0	1	0.04	0.20
LANG4 (foreign; non-national language at home)	18 283	0	1	0.13	0.11
ACTIVE (both parents economically active)	18 283	0	1	0.72	0.44
QWHITEC (white collar, highly skilled father)	18 283	0	1	0.33	0.45
NQWHITEC (white collar, low-skilled father)	18 283	0	1	0.14	0.34
QBLUEC (blue collar, highly skilled father)	18 283	0	1	0.33	0.45
NQBLUEC (blue collar, low-skilled father)	18 283	0	1	0.20	0.38
MOTSCY (years of schooling: mother)	18 283	3.5	16.5	10.53	3.96
FATSCY (years of schooling: father)	18 283	3.5	16.5	10.55	3.98
Household 2. Educational resources and their use					
NCOMPUT (dummy: 1 if no computer at home)	18 283	0	1	0.10	0.30
REGUSECO (student uses computers frequently)	18 283	0	1	0.70	0.42
SPUSECOM (student uses computers occasionally)	18 283	0	1	0.24	0.24
NUSECOM (student never uses computers)	18 283	0	1	0.06	0.46
REGWRITE (uses word processors frequently)	18 283	0	1	0.15	0.35
SPOWRITE (uses word processors occasionally)	18 283	0	1	0.76	0.42
NEVWRITE (never uses word processors)	18 283	0	1	0.09	0.28
25BOOKS (0–25 books at home)	18 283	0	1	0.17	0.37
100BOOKS (26–100 books at home)	18 283	0	1	0.33	0.47
200BOOKS (101–200 books at home)	18 283	0	1	0.22	0.41
500BOOKS (over 200 books at home)	18 283	0	1	0.27	0.44
School 1. School characteristics					
PUBLIC (public school)	18 283	0	1	0.62	0.48
PRIVPUBF (private school; publicly funded)	18 283	0	1	0.38	0.48
SCHSIZ (school size)	18 283	50	2 539	675.49	389.59
CITYSIZ1 (population $<$100 000)	18 283	0	1	0.61	0.49
CITYSIZ2 (population 100 000–1 000 000)	18 283	0	1	0.36	0.48
CITYSIZ3 (population $>$1 000 000)	18 283	0	1	0.03	0.16
NOTHERSC (maximum, 2 centres near the school)	18 283	0	1	0.32	0.46
School 2. Student characteristics					
ORIMMIG0 (school without immigrants)	18 283	0	1	0.48	0.50
ORIMMIG1 (0.1–10% immigrant students)	18 283	0	1	0.36	0.48
ORIMMIG2 (10–20% immigrant students)	18 283	0	1	0.10	0.31
ORIMMIG3 ($>$20% immigrant students)	18 283	0	1	0.05	0.23
SCEDMO (average years of schooling of mothers)	18 283	6.29	15.98	10.53	1.71
PCGIRLS (proportion of girls at school)	18 283	0.49	0.08	0	0.91
SCQWHITE (white collar, high skilled -mode-)	18 283	0	1	0.40	0.49
SCNQWHIT (white collar, low skilled -mode-)	18 283	0	1	0.02	0.13
SCQBLUE (blue collar, high skilled -mode)	18 283	0	1	0.45	0.50
SCNQBLUE (blue collar, low skilled -mode-)	18 283	0	1	0.13	0.34

Table A2 *Continued*

	N	*Min.*	*Max.*	*Mean*	*Standard dev.*
School 3. School resources					
STRATIO (student-teacher ratio)	18 283	1.19	30.55	11.74	4.37
PTEACH (proportion of part-time teachers)	18 283	6.73	6.98	0	79
CLSIZ (class size)	18 283	13	53	25.94	10.13
COMPWEB (proportion of computers with Internet)	18 283	0.07	1	0.89	0.17
IRATCO (computers for instruction/school size)	18 283	0.01	0.72	0.11	0.08
School 4. Educational practices					
NCOUNS (1 = no school counsellors at the centre)	18 283	0	1	0.20	0.39
AUTOHIRE (autonomy for selecting teachers for hire)	18 283	0	1	0.37	0.48
AUTBUDG (budgetary autonomy)	18 283	0	1	0.60	0.49
AUTEXT (autonomy for selecting textbooks)	18 283	0	1	0.95	0.23
AUTCONTE (autonomy for selecting contents)	18 283	0	1	0.57	0.49
AUTOCU (autonomy for modifying the curriculum)	18 283	0	1	0.54	0.50
CRITADMI (religious or philosophical issues are used as an admittance criterion)	18 283	0	1	0.30	0.45
STREB (ability grouping between classes)	18 283	0	1	0.48	0.47
STREW (ability grouping within classes)	18 283	0	1	0.44	0.46

Source: Own elaboration based on PISA-2006 data.

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