The Efficiency of Public and Publicly-Subsidized High Schools in Spain. Evidence from PISA-2006

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Abstract

The purpose of this paper is to compare 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 being 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 program (related to structural differences between management models), following the approach adopted by Silva Portela and Thanassoulis (2001). Once differences in students' background, 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.

Keywords: Efficiency; educational finance; resource allocation; PISA.

1. Introduction

One of the defining characteristics of the Spanish compulsory educational system is its mixed or dual nature i.e. a predominant public network but a substantial private sector. Within the latter, an important position is occupied by publicly-subsidized private schools (hereafter PSPS). PSPS, which account for 26% of secondary school enrolment in Spain, 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)[1]. 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 Spanish PSPS system is based on an administrative model which 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[2].

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 an exploration of the efficiency of such schools compared to public schools (hereafter PS). 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 is intended to answer, employing

[1] Student distribution among different school types in Spain is as follows: PS 67%, PSPS 26% and private-independent schools 7%.

[2] 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 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.

the data provided by the third wave of the Programme for International Student Assessment (PISA-2006), implemented by the Organization for Economic Co-operation and Development (OECD).

An initial examination of the average scores for PISA-2006 outcomes could lead to the conclusion that PSPS are more efficient than PS, since the crude (uncontrolled) results are higher in the former. 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 ANOVA test (5.89) 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 in the Appendix 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, Hoffer and Kilgore (1982) is commonly considered as the origin of this literature. The empirical methodologies used in this paper are hierarchical linear modeling (hereafter HLM) and data envelopment analysis (hereafter DEA). As far as we are aware, only a paper has employed these two methodologies jointly for measuring pupil and school attainment (see De Witte et al. 2010)[3].

[3] That paper 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 as complementary methods to analyse school and pupil performance. However, the present paper employs DEA and HLM sequentially. HLM allows us to estimate the underlying educational technology in the PISA-2006 data. Results from this part of the study are used to select the variables which are included in the subsequent DEA efficiency analysis.

Two aspects distinguish the present study from previous research. Firstly, special attention is paid to the empirical estimation of the underlying educational technology in the PISA-2006 data. The hierarchical structure of this dataset means that estimations must be performed via HLM. The conclusions extracted from these regressions allow us to select the variables for the subsequent DEA efficiency analysis in a robust empirical fashion. Secondly, our study decomposes the overall inefficiencies of each school into two components: managerial (resulting from its individual performance) and program (resulting from the structural differences between public and private management models). In order to perform this decomposition, we apply the approach of Silva Portela and Thanassoulis (2001), itself based on Charnes, Cooper and Rhodes (1981).

The rest of the paper is organized as follows. In Section 2 we review the literature devoted to studying the relationship between school efficiency and public or private ownership. The estimation of the determinants of educational outcomes in PISA-2006 is performed in Section 3. The empirical assessment of the efficiency of Spanish PS and PSPS is presented in Section 4, and the final section offers a summary of the principal conclusions.

2. The efficiency of public and private schools: previous studies

It is a fairly widely-held belief in certain academic and social circles that private schools are more efficient than public ones, an evaluation based upon the economic reasoning which links efficiency to free market competition.

For advocates of private schools, the competition which these schools are subjected to (both from within their own system and from public schools), due to their need to attract students, forces them to be highly receptive to their customers' demands and stimulates both an efficient use of resources and an improvement in the quality of the education provided (Chubb and Moe 1990; Friedman and Friedman 1981). It has been stated that the survival and economic success of private schools is strongly dependent upon their satisfying user desires and expectations, forcing them to act efficiently and effectively: *efficiently*, since otherwise what they provide will be at a disadvantage to the competition, and *effectively*, since if they do not satisfy their customers' demands, students may leave in search of better service (Alchian 1950). In short, the threat of closure faced by private schools, if badly managed, leads invisibly to such schools acting optimally.

By contrast, public schools are seen as monopolies at a local level, with a captive audience guaranteed by the criterion of assigning school places on the basis of residential area (Peterson 1990; Levin 1976; Pincus 1974; O'Donogue 1971). The opportunity for public school pupils to enroll elsewhere is therefore very limited, and would involve the "Tieboutian" method of "voting with your feet" (Tiebout 1956) which, apart from being very costly in economic terms, is strongly influenced by circumstances other than strictly educational ones. Furthermore, the alternative of changing to a private school is also strongly conditioned by the price differential between public and private supply, and thus, as Chubb and Moe (1990) point out, this option will only be adopted in cases where the value of private schools, as perceived by families, is much higher than that of public schools. Nor must we forget that this possibility is, of course, limited to the minority of the population with the greatest financial resources. These considerations have led various authors to consider that, in contrast to private schools, the achievement of efficiency and a satisfactory response to consumer demands is of merely secondary importance in public schools.

However, a more detailed analysis of schools' day-to-day functioning calls the above reasoning into question, since the ability of users in the education sector to exercise an informed choice – a key element for guaranteeing the potential benefits from competition– is very limited, given the ambiguous nature of the concept of school quality.

In fact, after almost forty years of research into the subject, our knowledge of the factors which contribute to defining what is a "good school" remains very sketchy (see Hanushek, 2003, 1997 and 1986). Schools are to a large extent still "black boxes" for the academics who research them, and even more so for their users. This is due to the peculiarities of the education system's production process, which makes it difficult to clarify the responsibilities attributable to schools and the definition of a representative concept of school quality (see Mancebón and Bandrés 1999). Given this context, the best way to assess how well a school functions is by direct contact with it. However, “trying out the product” in the educational sphere involves major personal costs, given the problems of adaptation which changing schools usually involves. This is what Glennerster (1991) terms the “sunk costs” associated with school choice.

The immediate consequence of this situation may be that individuals who must choose between different schooling alternatives do so on the basis of highly visible variables such as the religious leanings of the school, its facilities, its extra-curricular activities, the type of students attending, proximity to the home and so on. All of these factors are of a non-academic nature, and their relationship to the quality of the actual education provided has not been clearly established. On occasions, families may possess information concerning schools’ average academic results although, as Echols and Willms (1995) underline, these are inadequate indicators of quality unless accompanied by information on the academic and/or socio-economic background of pupils. Lee, Croninger and Smith (1996) discuss the problem of making decisions regarding education on the basis of virtually anecdotal or extremely superficial evidence of school quality, given that any other more thorough assessment would mean assuming significant information-related costs.

These limitations upon access to information regarding schools bring seriously into question the contention that competition has any effect upon the quality of schools, whether public or private, since users are unable to observe and measure such quality. The theoretical argument of those who defend private education, in the terms described above, is therefore questionable.

Additionally, empirical research devoted to clarifying the relationship between school efficiency and public or private ownership is not conclusive. The origins of this literature are in Coleman and others (1982) who, using cross-section achievement equations, 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 contrast this result in a wide range of educational contexts, through the use of parametric and non-parametric techniques. Such literature has offered mixed conclusions: while a number of studies tend to confirm the results obtained by Coleman and others (1982) (Opdenakker and Van Damme 2006; Bettinger 2005; Mizzala, Romaguera and Farren 2002; Bedi and Garg 2000; Stevans and Sessions 2000; Neal 1997; Jiménez, Lockheed and Paqueo 1991; Chubb and Moe 1990; Hanushek 1986), in others the presumed superiority of private schools vanishes when the analysis includes a wide range of controls (Perelman and Santin 2008; Mancebón and Muñiz 2008; Calero and Escardíbul 2007; Abburrà 2005; Fertig 2003; Kirjavainen and Loikkanen 1998; Goldhaber 1996; Sander 1996) or is reduced to specific measurements of the output analyzed (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, there exists a different effect for independent private schools and for PSPS (Dronkers and Robert 2008; Corten and Dronkers 2006). 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 and others (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.

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

This initial section is a first and necessary step for the correct selection of the input variables needed to feed the DEA analysis performed in the following section. Subsection 3.1 presents the literature review of the determinants of academic achievement. An econometric model is designed on the basis of this prior review, the results being presented in Subsection 3.3. Previously, Subsection 3.2 describes the data and methodology used in the analysis.

3.1. Determinants of educational outcomes: literature review

Our approach to the determinants of educational outcomes is structured by distinguishing between two levels, the first corresponding to student variables and the second to school variables. At the student level, we differentiate between three areas:

firstly, personal variables; secondly, variables related to the socio-cultural and economic characteristics of the family; and thirdly, variables related to household resources and their use. At the school level, four different areas are established: firstly, general variables describing the school; secondly, variables describing the school's students (and therefore the peer-effects generated by the interaction between students); thirdly, variables related to the human and physical resources used by the school and, finally, a fourth group of variables describing certain educational processes the school undertakes. On the basis of this structure, the present subsection reviews the effect of these variables upon educational outcomes, taking into account recent theoretical developments and the empirical evidence available in the literature.

At the student level, gender stands among the most important personal variables. Girls' school performance is usually better than boys'; however, 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 Calero and Escardíbul 2007; Chiswick and Debburman 2004; Kao and Tienda 1995; Rong and Grant 1992). 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 Dronkers (2008), Marks (2005), Gamoran (2001) and Rumberger and Larson (1998).

The final set of variables at the student level concerns household resources and how students use them (see Calero and Escardíbul 2007; Kang 2007; Woessman 2003). 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 in the household. Specifically, the availability of books in the household 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 we shall address. Here, one of the most relevant factors, from both a theoretical and empirical point of view, is ownership type i.e. private or public. Evidence in this area is far from conclusive, as Section 2 shows.

Several variables describing the characteristics of school students -or the classroom- are included in the second area of school level determinants. These characteristics influence, through peer effects, student performance. Authors such as Farley (2006), Willms (2006) and Coleman and others (1966) have analyzed the incidence of the socio-cultural and socio-economic profiles of peers upon student performance. This kind of approach has also been used to analyze 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. Kang (2007) and Hanushek and others (2003) describe how the negative effect of interaction with low-ability students is higher for this same group of low-ability students. Thus, processes of student grouping by ability level lead to negative effects on low-performing students. We could then expect the positive effect of grouping on high-performance students to be cancelled out by the negative effect on low-performance students, a situation which accounts for the results given by Gamoran (2004), who finds that these practices seldom produce the positive results expected.

3.2. Data and methodology

The present study uses PISA-2006 microdata for Spain. Since 2000, the PISA program has examined every three years the academic achievement of 15- year-old students from different countries[4] in three competencies (reading, mathematics and science). PISA focused, in the year 2006, on the competency 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 centers 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 centers 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 center

[4] 28 OECD and 4 non-OECD countries took part in PISA-2000. 14 non-OECD members joined the program in 2002. 41 countries participated in PISA-2003. 57 countries (30 OECD; 27 non-OECD) took part in 2006.

(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).

$$p_i = \frac{N_i . n_c}{N} \quad (1)$$

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.

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, due to the hierarchical structure of the PISA-2006 dataset[5]. The principle of the independence of variables among the students of each center is not maintained, as a consequence of the above-mentioned two-stage sampling method employed. Students enrolled in the same school usually share socio-economic circumstances which make the average correlation among the variables of students within the center to be higher than that found among students from different schools (Hox 1995)[6].

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

[5] Bryk and Raudenbusch (1988) provide a soundly-argued justification for the convenience of applying multilevel models to analyzing the effects of schools on educational outcomes.

[6] 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).

The present paper structures data into two levels: students (level 1) and centers (level 2). HLM allows the simultaneous analysis of the effects of variables of different levels and the influence of these variables on inequality within and between centers to be studied. In other words, HLM permits the identification of the proportion of the total variance in scholastic achievement which can be attributed to the characteristics of schools and students.

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

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

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

$$Y_{ij} = \gamma_{00} + \gamma_{10} X_{kij} + \gamma_{01} Z_{lj} + \mu_{1j} X_{kij} + \mu_{0j} + \varepsilon_{ij} \qquad (5)$$

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 $(\gamma_{00} + \gamma_{10} X_{kij} + \gamma_{01} Z_{lj})$ from a set of random effects $(\mu_{1j} X_{kij} + \mu_{0j} + \varepsilon_{ij})$.

The dependent variable is the science score for students enrolled in PS and PSPS[7]. This score is calculated using plausible values (PV hereafter) for each student and a replication method which permits efficient estimations to be obtained (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.

[7] Our sample includes 18,283 students from 643 schools. 61.8% of the students in the sample are enrolled in PS (61.4% of total schools) and 39.2% in PSPS. Students enrolled in non-subsidised private schools are not considered in our analysis.

3.3. Results

Table 2 presents the results corresponding to the multilevel regression: the first column lists the independent variables[8] introduced into the model, grouped into three blocks, individual, family or school. These variables have been included as a result of the theoretical approaches and empirical evidence described in Subsection 3.1. The second column presents the effects of these variables on PISA scores, following the same structure presented in Subsection 3.1 (two levels, divided into different areas). Table 3 provides information about 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.

The results for the individual level variables are consistent with previous empirical evidence. The fact that students born earlier in the year continue to display a comparative advantage is also noteworthy. 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.

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).	-65.8***
	Ref: Student enrolled in 4th year of compulsory secondary education	(-29.7)

[8] Further information about the independent variables is provided in Table A2 in the Appendix.

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

Area	Variable	Coefficient
Household 1. Socioeconomic 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)	-20.7**
	Ref: Born in Spain; Spanish parents	(-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)	2.7
	Ref: National student that speaks a national language at home	(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)	-8.5***
	Ref: White collar, high skilled father	(-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)	1.9
	Ref: Frequent use of computers	(-2.0)
	SPOWRITE (sporadic use of word processors)	7.7***
		(3.2)
	NEVWRITE (never uses word processors)	-16.0***
	Ref: Frequent use of word processors	(-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)	-9.1***
	Ref: More than 200 books at home	(-3.2)
School 1. School characteristics		
	PRIVPUBF (publicly subsidized private high school)	-15.2***
		(-1.7)
	SCHSIZ (school size)	-0.0
		(-0.1)
	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)

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

Area	Variable	Coefficient
School 2. Students characteristics		
	ORINMIG1 (proportion of immigrant students from 0,1 to 10%)	0.0 (0.0)
	ORINMIG2 (proportion of immigrant students from 10 to 20%)	-9.9* (-1.7)
	ORINMIG3 (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-) *Ref: White collar, skilled parents -mode-*	-3.2 (-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		
	AUTCONT (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

[a] *** 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)	1,221.8	411.9
Students (ε_{ij})	6,748.3	4,117.3
Total ($u_j + \varepsilon_{ij}$)	7,970.1	4,529.2
% 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.

Household socio-economic and cultural characteristics proved to be very important to the explanation of student performance in science. Results associated with the immigrant origin of the family are noteworthy: students born in Spain to Spanish parents obtain better results in the science test than first-generation immigrant students, although score differences compared to second-generation immigrants are not significant. This could be interpreted as evidence of a process of assimilating and integrating immigrant families, and is reinforced by the fact that 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 at least 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 worthy of note are those 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 would appear to be a suitable proxy for family cultural capital, and is strongly and positively correlated with 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 Mancebón and Muñiz (2008) and Calero and Escardíbul

(2007), found no significant differences in public and private school educational outcomes and, in the bivariate analysis, the former score lower than the latter.

According to the results, 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 their 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. Additionally, the proportion of girls at school is directly related to outcomes in PISA.

The only significant variables among the school resources factors included in our 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 counselors should help policymakers to measure 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, our 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 explained in Subsection 3.1.

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

In this section, an efficiency analysis of the PS and PSPS participating in PISA-2006 is performed, using DEA methodology. The analysis involves comparing 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 from its inputs results inferior to those potentially achievable.

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

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

The first stage in the performance of a productive efficiency analysis is the selection of the variables to proxy the results and inputs of evaluated decision-making units (DMUs). In this regard, the data supplied by PISA-2006 are plentiful. As explained in Section 3, this international program supplies detailed information about student competence in different subjects (mathematics, reading and science), their socio-economic and family background, and school inputs.

The prescriptions generally accepted in the DEA literature concerning variable selection establish that this must observe certain minimum requirements, as established by Bessent and Bessent (1980): a conceptual basis for the relationship of inputs to outputs; an empirically inferred relationship of measured inputs to outputs; increases in inputs must be associated with increases in outputs; and the measurements must not have zero elements.

In order to fulfill all these conditions, we base the selection of variables on the results obtained from empirical research into the determinants of educational outcomes in PISA-2006 (see Section 3). Specifically, we select the scores of 15-year-old students in science competencies as the output of Spanish PS and PSPS, and all the statistically significant variables described in the previous section as inputs (model 1)[9]. Table A3 in the Appendix summarizes the average and standard deviation for all these variables.

In summary, the efficiency of the Spanish PS and PSPS participating in PISA-2006 is estimated on the basis of 12 variables. One of these (PV) proxies output, two approximate the resources available to each school (IRATCO and CLSIZ) and the remaining nine proxy students' socio-economic and cultural background.

4.2. The selection of the DEA model

In addition to the choice of 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 seen notable growth, 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.

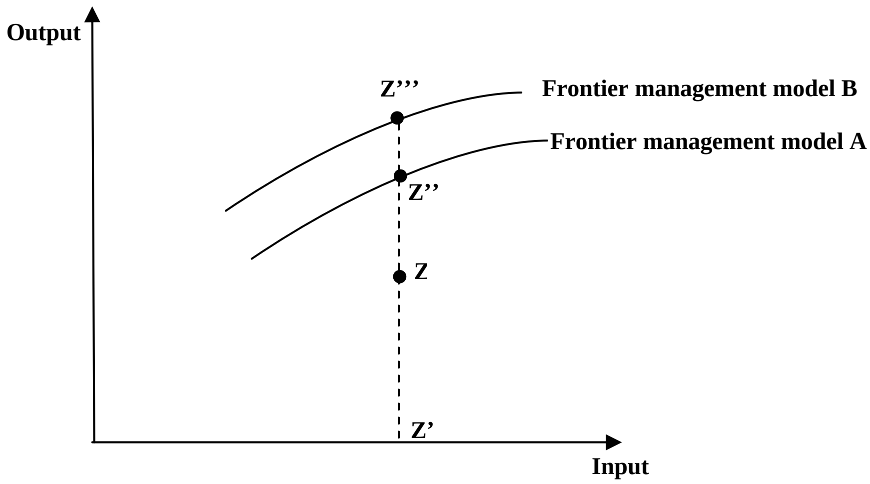
This technique, based on mathematical programming, has evolved considerably since it first appeared in the seminal paper of Charnes, Cooper and Rhodes (1978). Specifically, multiple extensions of the initial model have attempted

[9] We select those variables from the previous section which have been proved to be significantly influential upon academic outcomes in PISA and are non-categorical. Each input has been defined in such a way that its relationship to the output variable is positive. Below, we analyze three alternative specifications, in order to contrast the sensitivity of the DEA results.

to adapt the mathematical formulation and the process of obtaining efficiency indices to the peculiarities of the particular sector analyzed, to the nature of the variables constituting the analysis, or to the aims of the research in question (see Cooper, Seiford and Zhu 2004a, 2004b; Thanassoulis 2001).

From among the different proposals provided by the literature, the approach adopted by Silva Portela and Thanassoulis (2001), based on Charnes, Cooper and Rhodes (1981), is of particular interest for the task at hand. This approach decomposes the overall measurement of efficiency, computed using DEA, into managerial and program components. This approach is attractive, for it permits us to differentiate between inefficiencies attributable to the individual management of a decision-making unit (hereafter DMU) and those attributable to a unit’s management program. This property interests us greatly, since we are attempting to compare the behavior of schools employing different management models. We shall explain this approach using Figure 1.

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



This represents an organization (Z) which plays its productive role according to a specific management model (model A). Its efficiency is to be evaluated compared to a set of organizations, of which some employ the same management model (A) and the rest are guided by a different model (model B). The application of DEA to both 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 the management model for each), employing 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 due to individual school management and those attributable to the structural differences between the two management programs 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 i.e. 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, being the result of comparison with organizations functioning under the same management model, is attributable only to individual school practices.

Finally, Z's program efficiency will be the residual part of the overall efficiency not attributable to individual management. Graphically, this is determined by the index Z'Z'''/ Z'Z'' (maximum output in the sector/output which Z would use, if its individual management were efficient). We can thus immediately confirm that:

Overall Efficiency = (Managerial Efficiency) x (Program Efficiency) (6)

From this relationship the different efficiency indices may be computed by resolving three DEA models similar to that in Equation 7: one for DMUs employing model A (managerial efficiency of type A units); another for those guided by model B (managerial efficiency of type B units); and a third for all schools (overall efficiency of each organization). Program efficiency is obtained using a simple quotient between overall and managerial efficiency.

$$
\begin{aligned}
&Maximize : \theta_0 \\
&subject\ \text{to} : \sum_{j=1}^{n} \lambda_j x_{ij} \le x_{i0}, \qquad \text{i} = 1,2,...,\text{m} \\
&\qquad \sum_{j=1}^{n} \lambda_j y_j \ge \theta_0 y_0 \\
&\qquad \sum_{\text{j}=1}^{\text{n}} \lambda_j = 1 \\
&\qquad \lambda_{\text{j}} \ge 0
\end{aligned}
\tag{7}
$$

θ_0 is the efficiency score of each school, 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)[10].

5. Results of the efficiency analysis

Table 4 presents the results from the efficiency analysis performed according to the previously established criteria[11].

Table 4. Efficiency scores of inefficient schools

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

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

[10] Further details regarding the significance of Lambda values can be found in any reference book on DEA models, such as Cooper, Seiford and Zhu (2004a).

[11] The efficiency estimations were computed using ONFRONT software. The DEAs were performed under the variable returns to scale assumption (Banker, Charnes and Cooper 1984) and designed for assessing technical output efficiency.

The first row shows the efficiency rates resulting exclusively from the individual performance of each school. 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. This value has the greatest interest for the aims of the present research. Finally, the third row shows the estimations of overall efficiency i.e. 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 (program efficiency).

The results in Table 4 indicate that the difference between overall efficiency in PS and PSPS is very slight and statistically non-significant. That is to say, 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 allow us to correctly interpret the crude results obtained in this paper without first decomposing managerial and program efficiency. For example, it may be the case that even though differences in overall efficiency between PS and PSPS were not detected, the formers' management model could negatively affect their result, and that the individual performance of each PS compensates for the disadvantage of adopting a much more bureaucratic management model compared to PSPS.

To resolve this question, we must consider the results provided in the second row in Table 4 i.e. the efficiency due to structural differences between management models (program efficiency). Although overall efficiency values do not display great divergence, the differences found in this case become statistically significant in favor of PS. Additionally, the percentage of schools which display maximum overall efficiency (values in brackets in Table 4) is considerably higher among PS than PSPS, leading us to conclude that best practices are implemented by a higher proportion of PS than PSPS.

In order to contrast the robustness of these results we perform a sensitivity analysis. Such analyses are very important when using DEA, due to its non-parametric nature. We propose three alternative specifications for the previously solved model 1. We remove the variable CLSIZE (model 2), then the variable IRATCO (model 3) and, finally, remove education resources, CLSIZE and IRATCO (model 4). The effects of these variables upon educational outcomes are unclear, to judge by earlier literature (Hanushek 2003). Furthermore, we wish to analyze whether the differences found in program efficiencies between PS and PSPS are reduced when these resources are removed from DEA models.

Table 5. Program efficiency scores using alternative DEA models (inefficient schools)

	Mean efficiency			ANOVA test		
	PSPS	**PS**	**Total**	**Dif. on 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***

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

Table 5 displays the program efficiency scores for the four specifications described above. The results are robust in the four different models. Once differences in pupils background, school resources and individual management inefficiencies are removed, Spanish PS are more efficient than their PSPS counterparts.

6. 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, we believe 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 concerning the achievement of good results in science competencies. The only significant variables among the school resources factors included in our analysis were class size and the instructional computers/school size ratio.

These results, which confirm those of a number of previous studies, allowed us to further develop our efficiency analysis of PS and PSPS in Spain. The most important result was that PS are more efficient than PSPS; the better scores attained by PSPS in science competencies, as measured in PISA 2006, cease to exist when student characteristics and individual management inefficiencies are discounted. The results are robust in the different specifications of the DEA model, as shown by the sensitivity analysis.

This conclusion is in line with those reached in other, international, studies, where private high schools are shown to be inefficient compared to their public counterparts (Braun, Jenkins and Grigg 2006; Lubienski and Lubienski 2006; Barbetta and Turati 2003; Kirjavainen and Loikkanen 1998)[12].

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,

[12] A detailed discussion of this issue can be found in Lubienski, Weitzel and Lubienski (2009).

other papers employing PISA-2003 data for Spain indicate that neither PS nor PSPS are superior (Perelman and Santín 2008; Calero and Escardíbul 2007). 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 our work 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 our results[13]. 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.

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[13] In our view, 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.

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Appendix

Table A1. Student profiles in Spanish PS and PSPS

Type of variable	Questionnaire item	PSPS	PS	Total	ANOVA test
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***

[a] ***, ** and * indicate statistically significant mean differences between PSPS and PS at the 1%, 5% and 10% significance level, respectively.

[b] 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 centers near the school)	18,283	0	1	0.32	0.46
School 2. Student characteristics					
ORINMIG0 (school without immigrants)	18,283	0	1	0.48	0.50
ORINMIG1 (0,1-10% immigrant students)	18,283	0	1	0.36	0.48
ORINMIG2 (10-20% immigrant students)	18,283	0	1	0.10	0.31
ORINMIG3 (>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
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 counselors at the center)	18,283	0	1	0.20	0.39
AUTCONT (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 admitance criterion)	18,283	0	1	0.30	0.45
STREB (ability grouping between classes)	18,283	0	1	0.48	0.47
STREW (ability groupong within classes)	18,283	0	1	0.44	0.46

Source: Own elaboration based on PISA-2006 data.

Table A3. Variables used in the DEA model

Variable	Definition	PSPS		PS		Total	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
Output: PVS	Outcome in science (plausible value)	502.86	85.69	475.08	90.07	488.14	90.60
Input 1: NATIONAL	Percentage of students born in Spain	95.19%	0.76	90.04%	0.96	91.88%	0.68
Input 2: PCGIRLS	Proportion of girls at school	52.11%	2.01	48.64%	0.68	49.46%	0.72
Input 3: NOREPET	Percentage of students not repeating any grade	72.43%	1.26	51.19%	1.07	59.84%	0.85
Input 4: MOTSCY	Mother's years of schooling	10.39	4.43	8.80	4.67	9.63	4.73
Input 5: REGWRITE & SPOWRITE	Percentage of students using computers frequently or occasionally to create documents	89.64%	0.77	84.51%	0.87	86.82%	0.60
Input 6: QWHITEC	Percentage of students whose father's job is white collar highly- skilled	38.21%	2.07	22.30%	1.10	30.69%	1.00
Input 7: LANG1	Percentage of native students who speak national language at home	93.32%	0.79	87.19%	1.05	89.16%	0.75
Input 8: 500BOOKS	Percentage of students with over 200 books at home	28.32%	1.48	17.99%	0.86	23.95%	0.86
Input 9: ACTIVE	Percentage of students whose father and mother are both in active working population	73.83%	1.24	65.12%	1.02	68.98%	0.76
Input10: IRATCO	Ratio of instructional computers to school size (reverse)	15.93	0.04	8.36	0.10	9.96	0.09
Input 11: CLSIZ	Average class size	30.43	10.91	26.29	8.33	27.78	9.67

[a] Variables were redefined in such a way that their relationship with output was positive, a basic requirement of DEA models for the estimation of efficiency.

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