“The impact of school ownership in Spain. A regional analysis throughout unbiased parametric distance functions”

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Abstract

Last published results from PISA 2006 Report show that Spanish students have a poor performance according to test scores. However, there are significant differences among students attending publicly financed schools. The comparison among public and government dependent private schools (GDPS) could lead us to unfair conclusions because of possible school selection bias. In this paper we propose the use of a quasi-experimental Propensity Score Matching Approach in order to correctly analyse the impact of school ownership on student achievement. After tackling the self-selection problem we compare, using PISA 2006 data, student efficiency by school type across Spanish regions using parametric distance functions. To do this, we propose two original measures, the Average Treatment effect on the Treated on the Production Frontier (*ATTpf*) and assuming mean efficiency (*ATTpfe*). The general pattern shows that on average students benefit more of attending GDPS although there are wide divergences in student efficiency by school type and across regions.

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1. INTRODUCTION

One of the main goals in the field of economics of education is to analyze the efficiency in the learning processes. The sources of inefficiency may be due to multiple factors, so the lack of motivation or effort in both, students and teachers, pedagogical issues and the quality or experience of teachers influence any way on student performance and the educational inefficiency. However the role of organizational structure has focused most of attention in educational literature [*Nechyva* (2000), *Woessman* (2001)].

Regarding this point, different approaches from non-experimental to more recently randomized quasi experimental studies have been developed in order to analyze the importance of the school ownership on student's performance. There is widely-held belief in some academic circles about the students' results superiority of *GDPS* respecting to public ones. Some studies attribute the *GDPS* advantage to market competition, so these schools are forced to achieve a more efficient use of resources and offer a standard quality level to their students. Otherwise they may leave the school looking for another one that satisfies better their necessities [*Alchian* (1950), *Friedman and Friedman* (1981), *Chubb and Moe* (1990)]. Moreover, the students distribution across public financed schools is non linear, so *GDPS* students present a higher socioeconomic background. Similarly, students' results vary across regions, so own characteristic such as the local economic development and employment possibilities, immigrant population proportion, rural areas extensions and its educational policy differ among them. Consequently, some divergences on achievements could arise among regions and including about the effect of school ownership on academic results.

However there is no solid evidence about the superiority of any school type on achievements. Thus, some studies advocate for a private school advantage [*Witte* (1992), *Angrist et al.* (2002), *Krueger and Zhu* (2004), *Vandenberghe and Robin* (2004), *Duncan and Sandy* (2007)] whereas others do not find statistical differences among both school ownership [*Goldhaber* (1996), *McEwan* (2001), *Mancebón et al.* (2010)], or even few studies conclude that public education is significantly better than private one [*Kirjavainen and Loikkanen* (1998) and *Newhouse and Beegle*, (2006)].

The aim of this paper is to propose an alternative methodology for measuring educational efficiency by correcting the selection bias in public-financed school choice through a Propensity Score Matching (*PSM*) approach within the framework of stochastic frontier analysis. Schools which receive their core funding from government agencies are classified as either public or government dependent private schools (*GDPS*) according to whether a private entity or a public agency has the ultimate power to make decisions concerning its affairs. More in detail, public schools are controlled and managed by a public education authority or agency. On the other hand government dependent private schools are under a non-government organization or with a governing board not selected by a government agency which receive more than 50% of their core funding from government agencies[1].

The analysis of efficiency differences by school type becomes especially interesting in Spain, where students who attend to the public-financed system are distributed among both school types following a competitive process depending on personal students' characteristics[2]. However, this mechanism does not avoid certain practices that allow some families self-select themselves into the *GDPS*[3].

Up to the best of our knowledge *PSM* and stochastic frontier analysis have not been jointly used in any paper about the assessment of the school efficiency. Previously, a similar approach is implemented by *Mayen et al*. (2010) in order to compare productivity and efficiency of organic and conventional farms in Finland. To do this we estimate two stochastic parametric frontiers, one for each school type, for each Spanish region with representative sample in *PISA* 2006 from unbiased *PSM* subsamples. However, the measure of the impact of attending to *GDPS* with respect to public schools from *PSM* approach do not correctly reflect the true difference in students' results among both school types. This is because other relevant educational inputs and the efficiency component must be taken into account considering a stochastic production frontier framework in order to obtain a more robust indicator of this impact. Then, we propose two original measures, the Average Treatment effect on the Treated on the Production Frontier (*ATTpf*) and assuming mean efficiency (*ATTpfe*), which is, in our opinion, two more adequate indicators of the average impact of attending to a *GDPS*.

The poor results that Spanish students obtain in *PISA* 2006 compared to other European countries have intensified internal political debate about potential education policy measures that may enhance academic results [*Fuentes* (2009)]. This issue becomes even more interesting in Spain, where regions are fully responsible for the decision about the quantity of the educational budget and its allocation since 2000. For this reason this analysis allows us to evaluate potential efficiency divergences among regions within the same country and to analyze

1 There also exist government independent private schools controlled by a non-government organization or with a governing board not selected by a government agency which receive less than 50% of their core funding from government agencies. Although in this paper we focus only on schools publicly financed.

2 Having other siblings at school, the closeness of parents' home to the school and low family income have a positive impact in the school choice process.

3 In Spanish this is the so-called 'escuela concertada'.

the decentralization effect for regions which process took place in different periods of time. Thus, there is a mean gap of almost twenty years among regions which decentralization process in education was in the early eighties, as for example Andalusia, Catalonia, Galicia, Navarre and Basque Country, and other ones that it was in the late nineties: Aragon, Asturias, Cantabria, Castile-Leon and La Rioja. So we are interested in analyzing if the managerial experience presents a positive sign on the efficiency level reach in the case of previous decentralization and, at the same time, if arise some regional divergences about the impact of the school ownership on academic results.

Moreover, we use the student level as decision making unit to perform the analysis, which usually is aggregated at country [*Alfonso and St. Aubyn* (2006)], district [*McCarty and Yaisawarng* (1993), *Banker et al.* (2004)] or school [*Muñiz* (2002), *Cordero et al.* (2010)] level. Furthermore, considering separately student background and scholar resources we may test the influence of different school inputs across different school types [*Waldo*, 2007].

The paper is organized as follows. Section 2 provides an overview about the distance function and propensity score matching approaches together with our estimation strategy. In Section 3 data set and selected inputs and outputs from the Program for International Student Assessment (*PISA*) implemented in 2006 by the Organization for Economic Co-operation and Development (*OECD*) are described. Section 4 provides results and a discussion of our empirical analysis and the final section resumes main conclusions.

2. EDUCATION AND EFFICIENCY ACROSS PUBLIC AND GOVERNMENT DEPENDENT PRIVATE SCHOOLS

2.1. *Estimating an educational production function through distance functions*

The educational production function represents how schools produce educational outputs in the form of student achievement using facilities, equipment, teachers, students' own characteristics, peer-group interactions, supervisors and administrators. Following *Levin* (1974) and *Hanushek* (1986) this relationship can be defined:

$$A_{is} = f(B_{is}, S_{is}, P_{is}, I_{is}) \quad (1)$$

where A_{is} represents the achievement of student *i* at school *s*, usually represented by the results obtained in standardized tests. This output vector depends on a set of factors represented by socioeconomic background (B_{is}), mainly family characteristics, school inputs (S_{is}) such as educational material, teachers' characteristics or infrastructures in school, influence of classmates or peer-group effect (P_{is}) and the students' innate abilities (I_{is}).

Other factors related to the overall role of institutions, including main pedagogical choices, organizational structure and incentive schemes, among others, as well as motivation and effort of both teachers and students could influence on observed differences on students' results across schools. All these variables are difficult to capture and are gather into the efficiency component. Following Perelman and Santín (2008) we may estimate the educational multi-output multi-input production frontier assuming efficiency behaviors according to equation (2):

$$D_{is} = g\ (A_{is}, B_{is}, S_{is}, P_{is})I_{is} \qquad (2)$$

where g represents the best practice technology used in the transformation of educational inputs to outputs and D_{is} is the distance that separates each student i attending school s from the technological boundary. Unobservable student innate abilities, I_{is}, are assumed to be randomly normally distributed in the population[4] and to influence individual performance in a multiplicative way.

From Equation (2) we may identify divergences in performance and efficiency attribute to students and testing the statistical importance and the specific effect on students' attainment of all educational inputs considered in the educational production function.

For the empirical analysis it is common to assume a flexible *translog*[5] functional form to estimate the parametric distance function, which has been used previously in other studies such as *Grosskopf et al*. (1997) or *Coelli and Perelman* (1999, 2000). The translog distance function for the case of M outputs and K inputs adopts the following specification[6]:

$$\ln D_{oi}(x,y) = \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mi} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn} \ln y_{mi} \ln y_{ni} + \sum_{k=1}^{K} \beta_k \ln x_{ki} +$$
$$\frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} \ln x_{ki} \ln x_{li} + \sum_{k=1}^{K}\sum_{m=1}^{M} \gamma_{km} \ln x_{ki} \ln y_{mi} \qquad (i = 1,2,\ldots,N) \qquad (3)$$

[4] The scoring of modern IQ tests such as the Wechsler Adult Intelligence Scale [*Wechsler* (2008)], the primary clinical instrument used to measure adult and adolescent intelligence, is now based on a projection of the subject's measured rank on the normal distribution with a center value (average IQ) of 100, and a standard deviation of 15, although not all IQ tests adhere to this standard deviation.

[5] The Cobb Douglas form does not satisfy the concave imposition in the output dimension.

[6] The parameters of the distance function must satisfy some restrictions of symmetry and homogeneity of degree +1 in outputs, which implies that the distance of the unit to the boundary of the production set is measured by radial expansion.

where $x = (x_1, \ldots, x_K) \in \Re^{K+}$ and $y = (y_1, \ldots, y_M) \in \Re^{M+}$ are the educational input and output vectors respectively and sub-index i denotes the *ith* decision making unit in the sample. With the aim of obtaining the frontier surface, we set $D_o(x, y) = 1$, which implies that $\ln D_o(x, y) = 0$.

According to *Lovell et al*. (1994), normalizing the output distance function by one of the outputs is equivalent to imposing homogeneity of a degree +1. Then, rearranging terms, and following *Battese and Coelli* (1988) the expression of the traditional stochastic frontier model is as follows:

$$-\ln(y_{Mi}) = TL(x_i, y_i / y_{Mi}, \alpha, \beta, \gamma) + \varepsilon_i \quad (\varepsilon_i = u_i + v_i) \tag{4}$$

where the non-negative inefficiency random variable $u = -\ln D_{oi}(x, y)$ has a half-normal distribution $|N(0, \sigma_u^2)|$ and is independently distributed of the term v_i, which is independently and identically distributed as $N(0, \sigma_v^2)$.

However, simple maximum likelihood estimation of Equation (4) adding a dummy variable for identifying school type differences in performance may yield biased results due to several reasons. Firstly, the assignment of students across schools, at least in Spain, is not random. In principle, there are different legal criteria to accumulate points in order to chose a public financed school (public or *GDPS*). Main variables are low incomes and large size families, closeness of school to student resident, number of siblings at school and digestive problems.

However in practice we detect two main driving factors in favor of a selection process against low income and large size families. On the one hand, more motivated parents could take actions to self-select themselves into the *GDPS.* This is because of *GDPS* can freely assign one point to those children who have been attending the kindergarten attached to that school. Since all preschool education (0 to 2 years old) is run on a fully private basis, parents paying (by necessity) for these years of education are, in effect, “buying” this extra point. Moreover, some parents can temporally change their residence hiring a house closer to the school[7]. On the other hand, *GDPS* may impose rules to avoid low income students to achieve a better school and disciplinary climate. The most common practice to select students from high income families is to ask parents for a *voluntary monthly fee* (varying from 50 € to 300 € per month and child) sometimes justified to offer some extra-curricular activities. As a consequence, families not able to afford these

[7] Even it is possible to find parents that lie about their family’s circumstances (declaring that both parents live separated in different municipalities) or giving false certificates about the child health.

fees self-select themselves sending their children to public schools. Although, it is possible some students from high income families attend to public schools leading by certain ideology criteria or because they do believe that public school teachers are better prepared[8]. Hence, similar students could be found in both public and *GDPS* schools, although the variability of the student's background is wider for public ones.

In order to measure the impact of school type attendance on student's achievement we need to use a 'quasi-experimental' evaluation technique. In order to obtain the true effect of the school type on student's performance would be necessary to compare the result of the same student in both, *GDPS* and public schools. However in real life it is only possible to observe the student's attainment in one school. To overcome this trouble a counterfactual[9] of each *GDPS* student (treated) must be sought among public school students (non-treated).

Different alternatives have been used in the literature to tackle the self-selection in education named above such as instrumental variables (*IV*), Heckman's two stage and *PSM* non-experimental approaches or randomized lotteries. Nevertheless, the estimation of both *IV* and Heckman methodologies requires the identification of suitable instruments [*Goldberger* (1983), *Puhani* (2000)] what is a difficult issue for a properly implementation. Additionally these approaches assume a constant impact of the school type effect over students' results regardless the distribution of variables included in Equation (2). To overcome these difficulties we propose the use of *PSM* technique.

The aim of *PSM* is to find in a large group of non-treated, those individuals that are similar to the treated, conditioning on a set of observable variables *X* that solve the selection bias[10] [*Rosembaum and Rubin* (1983), *Heckman and Navarro–Lozano* (2004)]. In order to implement it, firstly we estimate the probability of attending to a *GDPS* (propensity score) for each student through a logit analysis.

$$S_i = Z_i.\gamma + \xi \tag{5}$$

[8] To become a teacher in a public school it is required to pass a state exam while to teach in a *GDPS* only a three years university degree is required.
[9] A student who attends public school is counterfactual of a *GDPS* student if both have similar personal and family characteristics.
[10] We know that other unobservable characteristic could influence on the school choice, which suppose that the selection bias would not be corrected, but it is not possible to test.

where S_i equals one if the student attends to a *GDPS* and zero otherwise, *Zi* is a vector of observable characteristic that determine the school choice, γ is a set of parameters that must be estimated and ξ is the error term. Secondly we use the previous estimated probabilities to obtain matched pairs of a treated individual with his most similar counterfactual[11]. After obtaining the matched subsample, the average impact of attending to a *GDPS* on students' results is calculated through the Average Treatment effect on the Treated (*ATT*) following the expression above:

$$\tau_{ATT} = E\{E[Y_i\ (1)|S_i = 1, p(X_i\ )] - E[Y_i\ (0)|S_i = 0, p(X_i\ )]|S_i = 1\} \tag{6}$$

where $Y_i(1)$ and $Y_i(0)$ are the achievement in both *GDPS* and public schools respectively, supposing the two counterfactual situations of treatment (attending to a *GDPS*) and no treatment (attending to a public one), X_i is a multidimensional vector of observable characteristic that determine the school choice and p(X_i) is the probability of attending to a *GDPS*.

2.2. Our strategy

According to the aim of this paper we propose a new framework to analyze efficiency component in education, which allows us to obtain unbiased students' results comparisons among different school types. Two alternative approaches are combined in order to obtain unbiased students' results comparisons among different school types. For that purpose, firstly, the *PSM*[12] approach is implemented to obtain unbiased subsamples of treated and non-treated students for each Spanish region with representative sample in *PISA* 2006. Then in a second step, two production frontiers at student level, one for each school type and region, are modeled through the parametric distance function approach, assuming different technologies in both school types.

[11] Both balancing and independency properties are necessary to the correct implementation of *PSM*. For more detail see *Caliendo and Kopeing* (2005).
[12] Instrumental variables and Heckman methodologies are used in the literature to deal with this selection problem but both requires the identification of suitable instruments [*Goldberger* (1983), *Puhani* (2000)] what is a difficult issue for a properly implementation.

Our proposal consists of a three stage procedure. In a first step, we estimate the *ATT* for each regional sample and discipline using the nearest neighbor estimator[13] in order to obtain the matches pairs:

$$ATT_D^R = E\{E[Y_i^R(1)|S_i = 1, p(X_i^R)] - E[Y_i^R(0)|S_i = 0, p(X_i^R)]|S_i = 1\} \qquad (7)$$

where sub-index *D* indicates the corresponding output (test score in *PISA*) and upper-index *R* corresponds to each region.

In a second step, we estimate two stochastic educational production frontiers, one for each regional matched-sample. This procedure allows us to obtain a new measure, the Average Treatment effect on the Treated on the Production Frontier (*ATTpf*), as the difference between both mean predicted output in the production frontier in each discipline for *GDPS* and public schools students in each region.

$$ATT_{pf}^R = E\left[\hat{y}_{i,C}^R\right] - E\left[\hat{y}_{i,P}^R\right] \qquad (8)$$

where *C (P)* refers to *GDPS* (public) schools students and $\hat{y}_i^R$ is the mean educational output vector in each production frontier and region. This indicator allows us to incorporate all relevant inputs involved in the educational process that were not considered in the *ATT* estimation assuming that all students and schools are fully efficient.

Finally, in order to allow mean divergences in efficiency among schools, we define the Average Treatment effect on the Treated on the Production Frontier assuming Efficiency (*ATTpfe)*, being the expression for each discipline and region as follows:

$$ATT_{pfe}^R = \left\{E\left[\hat{y}_{i,C}^R\right]\cdot \bar{u}_C^R\right\} - \left\{\left[\hat{y}_{i,P}^R\right]\cdot \bar{u}_P^R\right\} \qquad (9)$$

where $\bar{u}_c$ and $\bar{u}_P$ are the mean estimated student efficiencies in both *GDPS* and public schools in each region respectively.

[13] There exist several approaches to obtain the matches, although the analysis of these alternatives excesses the aim of this paper. For more insight on this topic see *Heckman et al*. (1997).

Figure 1 illustrates these three measures in a simple two-output one input setting, where *Pr* (*Pb*) represents the *GDPS* (public) school frontier. Let assume that A and B are two different students attending to different types of school according to their ownership. The difference between the two outputs produced by students A and B corresponds with the *ATT* for outputs y_1 and y_2. Then, after considering other factors that are involved in the educational production process, as well as technical efficiency, we can project both students, A and B, to their respective production frontiers (C and D), being the difference between the two outputs in points C and D the *ATTpf* for outputs y_1 and y_2. Finally, allowing different average student inefficiencies among both *GDPS* and public schools, the *ATTpfe* is the difference between the outputs obtained in points E and F for outputs y_1 and y_2.

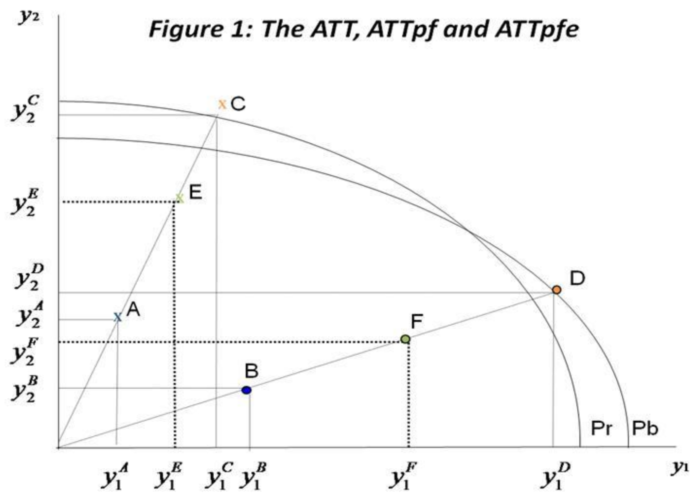


Figure 1: The ATT, ATTpf and ATTpfe

3. ANALISYS OF SPANISH EDUCATION IN *PISA* 2006

3.1. Data

In our empirical analysis, we use Spanish data from *PISA* 2006 evaluation which provides us with data from 15 years old students belonging to ten regions that decided to take part in evaluation with an extended representative sample of their population (Andalusia, Aragon, Asturias, Cantabria, Castile-Leon, Catalonia, Galicia, La Rioja, Navarre and Basque Country). The methodology described in section 2.2. is carried out for each region separately. It is worth noting again here, that the Spanish regions are actually fully responsible for the management of educational resources since 2000. Therefore, they should be the ones most interested in analyzing *PISA* results as a previous step for the application of more effective educational policies. To perform this analysis, we have data from 15,918 students and 564 schools distributed across ten regions as shown in Table 1.

Table 1: Distribution of students and schools by ownership and region

Region	*Students*	*Public*	*GDPS*
Andalusia	1,419	37	13
Aragon	1,376	31	16
Asturias	1,318	31	14
Cantabria	1,385	31	19
Castile-Leon	1,369	31	17
Catalonia	1,149	29	11
Galicia	1,381	36	11
Navarre	1,489	22	20
Rioja	1,240	30	19
Basque Country	3,797	63	83
TOTAL	**15,923**	**341**	**223**

Source: *PISA* 2006 Report for Spain

3.2. Variables

Control variables for the PSM analysis

In order to calculate the *ATT* in each region for analyzing the impact of attending to a *GDPS* we have used a set of control variables that allow us to obtain the matched pairs in the previous propensity score stage[14]. These variables are directly correlated with the parent's school ownership choice (*Pared, Hisei, Immigrant* and *City*), being *School* the dummy variable of treatment[15].

Pared and *Hisei* represent the index scores for the highest educational[16] and occupational level of parents respectively. Both variables were recoded into estimated years of schooling and the highest occupational status for both the student's father and mother

[14] As a consequence of imposing balancing property to ensure that only students with the same probability of attending to a *GDPS* are matched, the total sample size reduces from 15,918 to 15,123 students.

[15] *PSM* are calculated using *Pared, Immigrant* and *City* as control variables in all regions, with the exception of Castile-Leon and Basque Country where *Hisei* is used instead of *Pared* to impose the balanced property.

[16] Parental education is classified using *ISCED* (*OECD*, 2000). Indices on parental education are constructed by recoding educational qualifications into the following categories: (0) None; (1) *ISCED* 1 (primary education); (2) *ISCED* 2 (lower secondary); (3) *ISCED* Level 3B or 3C (vocational/pre-vocational upper secondary); (4) *ISCED* 3A (upper secondary) and/or *ISCED* 4 (non-tertiary post-secondary); (5) *ISCED* 5B (vocational tertiary); and (6) *ISCED* 5A, 6 (theoretically oriented tertiary and post-graduate).

respectively. Many studies support the evidence of the influence of socio-economic background as determinant of the educational outcome [*Witte* (1998), *McEwan* (2001), *Sander* (2001), *Dronker* (2008), *Perelman and Santín* (2008), *Mancebón et al*. (2010)].

Immigrant condition. This factor, whose influence has received increasing attention in literature within the last years [*Witte* (1998), *Gang and Zimmermann* (2000), *Entorf and Minoiu* (2005), *Cortes* (2006), *Schnepf* (2008)], becomes especially interesting for Spain due to the huge growth undergone by immigrant population at school age during the last decade[17]. In view of this phenomenon, several studies have analyzed recently the influence of this factor on the results of Spanish students by using information provided by *PISA* database [*Chiswick and DebBurman* (2004), *Calero and Escardibul* (2007), *Zinovyeva et al.* (2008), *Calero and Waisgrais* (2009), *Mancebón et al*. (2010)]. In our study, this factor has been included in both *PSM* and efficiency analysis through three dummy variables: *Immigrant*, which is considered in the *PSM* analysis, takes value one when the student and/or his parents was/were born abroad and zero otherwise.

City, which represents the community size where the school is located, takes value one if the community is a large city or a city and zero if the school is located in a town, small town or village[18]. Following *Vandenberghe and Robin* (2004), who showed positive influence of household location on school choices, we consider it as a control variable in the *PSM* analysis following the same approach of several studies [*McEwan* (2001), *Sander* (2001), *Perelman and Santín* (2008)].

School takes value one for *GDPS* school students and zero for public school ones. This variable is the treatment variable in the *PSM* estimation in order to obtain pairs of treated and counterfactual individuals. The influence of this variable on student achievement is not clear, then some studies show a better performance for *GDPS* school students [*Chubb and Moe* (1990), *Sander* (1996), *Figlio and Stone* (1997), *Neal* (1997), *McEwan* (2001)] whereas others do not find enough evidence to justify this superiority [*Witte* (1992), *Goldhaber* (1996), *Vandenberghe and Robin* (2004), *Mancebón and Muñiz* (2007)].

[17] According to Spanish official statistics captured by *MEC* (2008), foreign students in non-university education have grown from a total number of 72,335 in 1998 to 695,190 in 2008.

[18] The population size for a village, hamlet or rural area is fewer than 3, 000 people; 3, 000 to about 15, 000 people in a small town; 15,000 to about 100, 000 people in a town; 100, 000 to about 1,000, 000 people in a city and for a large city with or over 1,000, 000 people.

Inputs for the parametric distance function approach

On the other hand, we have used five different inputs for the distance function estimation described in Equation 3 (*Scmatedu, Escs, Peer, Pcgirls and Stratio*) together with six control factors (*Rep, Repmore Schsize, Firstgen, Secgen and Gender*) that do not interact with other variables. All of them are directly involved with the student learning process.

Scmatedu[19] represents the quality of scholar resources. This variable is an index derived from school principals' responses to seven items related with the availability of educational resources such as computer for didactic uses, educational software, calculators, books, audiovisual resources and laboratory equipment. Respecting to the role of the school's resources on academic result there is a wide and no conclusive literature. Then, while some studies show a positive influence [*Carroll* (1963), *Krueger* (1999)], others support there is no direct correlation between more school inputs and better academic outcomes [*Hanushek* (1986, 1997, 2003)].

Escs reflects the s*ocio-economic background* of each student. It is an index of economic, social and cultural status of students created by *PISA* analysts from three variables related to family background from students' questionnaire: the index of highest level of parental education in number of years of education according to the *International Standard Classification of Education* [*ISCED*, *OECD* (1999)], the index of highest parental occupation status according to International Socio-economic index of Occupational Status [*ISEI*, *Ganzeboom et al*. (1992)] and the index of educational possessions at home. On the other hand, *Peer* incorporates information about classmates' characteristics of students[20]. This variable is defined by the average of *Escs* variable of students that share the same school with the evaluated one.

Pcgirls is an index of the proportion of girls at school that is based on the enrolment data provided by the school principal, dividing the number of girls by the total of girls and boys at the school. We introduce this variable in order to test if higher proportions of girls imply better academic results [*Calero and Escardibul* (2007), *Calero et al*. (2010)].

Classroom size (*Stratio*) is a ratio between total number of students in school and total number of teachers weighted on their dedication[21]. This variable is usually considered a school input in efficiency analysis according to the results of some studies in which a direct

[19] Since positive and negative values can be found in the original variable, we have re-scale all the values in order to have only positive values for the input variables.
[20] For a review of the effect of these variables over results see *Betts and Shkolnik* (2000) or *Hanushek et al.* (2001).
[21] Part-time teachers contributes 0.5 and full-time teachers 1.

relationship is found between reduced groups and higher academic performance [*Card and Krueger* (1992), *Hoxby* (2000), *Krueger* (2003), *Mora et al.* (2010)]. However, other studies conclude that this variable is not significant [*Hanushek* (1997, 2003), *Pritchett and Filmer* (1999)].

Repeat once (Rep) and *Repeat more (Repmore)* are two dummy variables that represent those students that have repeated one or more courses respectively. This phenomenon is quite important in the case of Spain, where the repetition rate is much higher than in other countries in the *OECD*[22] [*Fuentes* (2009)]. Again the effect of this policy on educational results is controversial. Thus, literature contains studies finding certain positive relation [*Pierson and Connell* (1992), *Roederick et al.* (2002)], although most studies conclude that the repetition leads to a reduction of academic performance and considerably increases students' dropout probabilities [*Holmes and Mathews* (1984), *Shepard et al.* (1996), *Alexander et al.* (2003)].

School size (*Schsize*) indicates the total number of students in school. The influence of this variable in the educational process has also been tested in previous studies, in which we can find results supporting that schools with more students have better results [*Bradley and Taylor* (1998), Barnett *et al.* (2002)], but also other that conclude that this factor does not affect the results [*Hanushek and Luque*, 2003] or find that lower class sizes reduce the rate of dropout and the proportion of early school-leaving [*Mora et al.*, 2010].

Firstgen points out that the student and almost one of his/her parents were born abroad and *Secgen* when the student was born in Spain but at least one of his/her parents was born abroad, that allows us to identify the first and second generation immigrant.

Gender, that takes value one for girls and zero for boys, is considered one of the most important personal variables in educational process. Several studies, such as *Calero and Escardibul* (2007) and *Mancebón et al.* (2010) in Spain, find a better performance on reading for girls, but just the opposite on mathematics and science, where boys get higher results from *PISA* 2006.

Tables 2-3 report the average inputs for public and *GDPS* schools in each region. These figures show that students who attend to *GDPS* schools present a higher socioeconomic background, as we expected. Likewise the student-teacher ratio and the school size is always lower in public schools, while the proportion of immigrant and repeater students or the quality

[22] In Spain more than 40% of students have repeated a course almost once.

Table 2: Descriptive statistics of matching GDPS schools inputs sample

Region	Obs	*Variable*	*Pared*	*Hisei*	*Immigrant*	*City*	*Scmatedu*	*Escs*	*Peer*	*Pcgirls*	*Rep*	*Repmore*	*Stratio*	*Schsize*	*Primgen*	*Seggen*	*Gender*
Andalusia		Mean	11.303	47.950	0.003	0.470	2.071	5.872	5.869	0.498	0.229	0.119	19.468	841.507	0.000	0.003	0.521
	353	Std. Dev.	4.251	18.402	0.053	0.500	0.514	1.129	0.585	0.047	0.421	0.324	2.018	483.617	0.000	0.053	0.500
Aragon		Mean	12.402	49.975	0.022	0.729	2.583	6.154	6.153	0.493	0.195	0.042	17.017	855.987	0.018	0.004	0.499
	451	Std. Dev.	3.654	17.004	0.147	0.445	0.993	0.976	0.468	0.095	0.397	0.201	2.266	557.589	0.132	0.067	0.501
Asturias		Mean	12.492	47.258	0.016	0.428	2.218	6.055	6.051	0.498	0.238	0.056	16.081	751.029	0.013	0.003	0.513
	374	Std. Dev.	3.410	17.025	0.126	0.495	0.889	0.951	0.453	0.051	0.426	0.231	2.693	501.586	0.115	0.052	0.500
Cantabria		Mean	12.419	45.248	0.037	0.434	2.078	6.072	6.071	0.497	0.239	0.041	17.163	704.213	0.035	0.002	0.509
	489	Std. Dev.	3.460	0.000	0.188	0.496	0.753	0.994	0.525	0.064	0.427	0.198	2.838	302.689	0.183	0.045	0.500
Castile		Mean	12.540	45.248	0.026	0.373	2.305	6.154	6.155	0.498	0.247	0.050	16.251	701.421	0.026	0.000	0.507
Leon	458	Std. Dev.	3.551	0.000	0.160	0.484	0.944	0.972	0.438	0.094	0.432	0.219	2.211	431.144	0.160	0.000	0.501
Catalonia		Mean	11.642	46.597	0.064	0.631	2.398	5.885	5.872	0.480	0.192	0.015	15.856	754.527	0.052	0.012	0.512
	328	Std. Dev.	3.555	15.368	0.245	0.483	0.925	0.906	0.297	0.043	0.395	0.123	1.374	295.677	0.222	0.110	0.501
Galicia		Mean	12.152	49.863	0.024	0.409	1.935	6.131	6.133	0.462	0.193	0.078	15.554	609.689	0.003	0.020	0.453
	296	Std. Dev.	3.702	16.843	0.152	0.492	0.703	1.018	0.600	0.056	0.395	0.268	1.971	311.797	0.058	0.141	0.499
Navarre		Mean	13.221	52.487	0.046	0.636	1.946	6.306	6.295	0.481	0.152	0.033	13.843	893.970	0.041	0.005	0.494
	605	Std. Dev.	3.387	18.144	0.210	0.481	0.630	0.980	0.541	0.128	0.359	0.179	3.521	472.156	0.199	0.070	0.500
Rioja		Mean	12.633	50.973	0.032	0.659	2.237	6.261	6.257	0.462	0.188	0.032	17.188	638.915	0.032	0.000	0.458
	563	Std. Dev.	3.501	17.456	0.176	0.474	0.848	0.987	0.432	0.151	0.391	0.176	2.288	404.291	0.176	0.000	0.499
Basque		Mean	13.024	49.991	0.016	0.432	2.721	6.187	6.186	0.466	0.141	0.019	15.348	1016.255	0.015	0.001	0.495
Country	2,255	Std. Dev.	3.368	17.252	0.124	0.496	0.762	0.955	0.499	0.092	0.349	0.135	2.949	534.189	0.120	0.030	0.500
TOTAL	**6,172**	***Mean***	**12.383**	**48.559**	**0.029**	**0.520**	**2.249**	**6.108**	**6.104**	**0.484**	**0.201**	**0.048**	**16.377**	**776.751**	**0.024**	**0.005**	**0.496**
		Std. Dev.	**3.584**	**13.749**	**0.158**	**0.485**	**0.796**	**0.987**	**0.484**	**0.082**	**0.399**	**0.205**	**2.413**	**429.473**	**0.137**	**0.057**	**0.500**

Source: Personal compilation based on *PISA* 2006 data for Spain

Table 3: Descriptive statistics of matching public schools inputs sample

Region	Obs	*Variable*	*Pared*	*Hisei*	*Immigrant*	*City*	*Scmatedu*	*Escs*	*Peer*	*Pcgirls*	*Rep*	*Repmore*	*Stratio*	*Schsize*	*Primgen*	*Seggen*	*Gender*
Andalusia		Mean	9.475	40.163	0.005	0.292	3.887	5.337	5.346	0.503	0.355	0.082	11.241	633.413	0.002	0.003	0.527
	1,039	Std. Dev.	4.135	14.561	0.069	0.455	1.082	0.983	0.414	0.043	0.479	0.274	1.477	271.540	0.044	0.054	0.499
Aragon		Mean	11.439	44.202	0.081	0.487	2.439	5.771	5.774	0.516	0.341	0.078	9.520	613.748	0.076	0.005	0.491
	924	Std. Dev.	3.849	16.638	0.273	0.500	0.773	0.999	0.380	0.065	0.474	0.268	1.756	305.886	0.265	0.073	0.500
Asturias		Mean	11.711	42.807	0.026	0.359	3.357	5.744	5.738	0.511	0.273	0.057	7.906	576.977	0.021	0.004	0.490
	941	Std. Dev.	3.528	15.864	0.158	0.480	1.005	0.952	0.338	0.067	0.446	0.233	1.012	217.041	0.144	0.065	0.500
Cantabria		Mean	11.575	43.058	0.031	0.195	2.386	5.780	5.776	0.509	0.328	0.069	8.145	548.079	0.030	0.001	0.500
	894	Std. Dev.	3.477	15.953	0.174	0.396	0.756	0.905	0.280	0.082	0.470	0.254	1.318	205.174	0.171	0.033	0.500
Castile		Mean	11.444	41.792	0.029	0.305	3.067	5.693	5.679	0.493	0.323	0.060	9.415	668.203	0.028	0.001	0.460
Leon	902	Std. Dev.	3.736	0.000	0.167	0.461	0.935	0.968	0.357	0.064	0.468	0.237	1.942	336.914	0.164	0.033	0.499
Catalonia		Mean	11.040	43.231	0.079	0.326	2.832	5.664	5.627	0.487	0.287	0.035	9.556	505.611	0.070	0.009	0.516
	773	Std. Dev.	4.045	15.676	0.270	0.469	1.051	0.962	0.336	0.044	0.453	0.184	1.001	141.844	0.255	0.095	0.500
Galicia		Mean	10.671	40.505	0.023	0.161	2.708	5.506	5.504	0.502	0.318	0.115	8.197	459.602	0.018	0.006	0.484
	1,084	Std. Dev.	3.765	14.736	0.150	0.368	0.982	0.964	0.417	0.088	0.466	0.320	1.637	192.966	0.131	0.074	0.500
Navarre		Mean	11.407	42.516	0.072	0.275	2.800	5.691	5.679	0.511	0.260	0.040	8.477	547.716	0.068	0.003	0.520
	877	Std. Dev.	3.752	15.697	0.258	0.447	1.003	0.932	0.312	0.047	0.439	0.196	1.312	307.386	0.253	0.058	0.500
Rioja		Mean	11.180	42.498	0.074	0.377	2.446	5.716	5.713	0.496	0.337	0.058	9.353	592.794	0.068	0.006	0.528
	676	Std. Dev.	3.708	15.153	0.262	0.485	0.858	0.922	0.282	0.070	0.473	0.233	1.578	306.517	0.252	0.077	0.500
Basque		Mean	12.204	45.766	0.066	0.318	2.868	5.872	5.869	0.491	0.250	0.056	6.980	446.905	0.061	0.005	0.513
Country	1,541	Std. Dev.	3.817	16.736	0.249	0.466	1.068	0.975	0.460	0.072	0.433	0.230	1.413	230.598	0.239	0.072	0.500
TOTAL	**9,651**	***Mean***	**11.215**	**42.654**	**0.049**	**0.309**	**2.879**	**5.677**	**5.670**	**0.502**	**0.307**	**0.065**	**8.879**	**559.305**	**0.044**	**0.004**	**0.503**
		Std. Dev.	**3.781**	**14.101**	**0.203**	**0.453**	**0.951**	**0.956**	**0.358**	**0.064**	**0.460**	**0.243**	**1.445**	**251.587**	**0.192**	**0.063**	**0.500**

Source: Personal compilation based on *PISA* 2006 data for Spain of scholar resources is usually higher, with the exception of Andalusia and Aragon, being the only regions where repeating several years and the quality of scholar resources is higher in *GDPS* schools respectively. Finally, we highlight that these inputs differences among both school types are not so wide in Catalonia.

Outputs and plausible values

The true educational output is very difficult to measure empirically due to its inherent intangibility, so education does not only consist of the ability of repeating information and answering questions, but it also involves the skills to interpret the information and learn how to behave in the society. In spite of the multi-product nature of education, most studies have used the results obtained in cognitive tests since they are difficult to manipulate and respond to administration demands. But perhaps, according to *Hoxby* (2000), the most important reason could be that both policy makers and parents use this criterion to evaluate the educational output and its subsequent information to choose the school for their children and even their place of residence.

In this study we use the results obtained by students in the three competences evaluated in *PISA* (mathematics, reading comprehension and sciences) as the vector of educational output. One of the main advantages of the *PISA* study is that it does not evaluate cognitive abilities or skills through using one single score, so each student receives a score in each test within a continuous scale. On the other hand, *PISA* uses the concept of plausible values to measure the performance of students, corresponding with five random values from the students' results distribution in each discipline[23]. This approach let us to consider the wide margin of error in the measure of students' results due to the fact that these measures are abstract and subject to the special circumstances of students and their environment on the date of their exams.

Table 4 reports the average plausible values[24] for the three tests (mathematics, reading comprehension and sciences) in both public and *GDPS* schools after controlling the self-selection bias. Five different plausible values in the three tests are used as outputs in the *PSM* and efficiency analysis respectively. In order to obtain unbiased results five different efficiency analysis for each trio of plausible values are estimated and take the average value afterwards, instead of using mean values to obtain only one efficiency measure [*OECD* (2005)]. Similarly,

[23] For a review of plausible values literature see *Mislevy et al.* (1992). For a concrete survey of *Rasch* model and how to obtain feasible values in *PISA*, see *OECD* (2000).
[24] From now and for presentation purposes we only report the mean results of analyzing the five plausible values in each discipline.

five different *ATT* measures for each plausible value and region are calculated to obtain the mean value afterwards.

Table 4: Descriptive statistics of PSM outputs sample

			GDPS schools					*Public schools*		
	Obs		*Math*	*Read*	*Scie*	*Obser*		*Math*	*Read*	*Scie*
Andalusia	*353*	*Mean*	478.04	464.88	485.35	*1,039*	*Mean*	466.77	447.34	479.58
		Std. Dev.	83.50	81.93	85.45		*Std. Dev.*	83.55	85.82	87.32
Aragon	*451*	*Mean*	521.58	492.70	525.24	*924*	*Mean*	506.82	475.76	505.87
		Std. Dev.	93.53	84.38	82.38		*Std. Dev.*	97.99	87.88	89.92
Asturias	*374*	*Mean*	498.65	491.21	517.68	*941*	*Mean*	495.29	472.54	503.05
		Std. Dev.	78.82	81.76	79.98		*Std. Dev.*	80.19	82.15	82.05
Cantabria	*489*	*Mean*	508.46	485.44	519.29	*894*	*Mean*	504.13	474.90	509.47
		Std. Dev.	79.65	80.93	82.86		*Std. Dev.*	87.38	86.38	85.07
Castile	*458*	*Mean*	527.12	499.62	531.54	*902*	*Mean*	512.87	472.73	519.65
Leon		*Std. Dev.*	76.50	72.21	76.42		*Std. Dev.*	83.50	75.30	80.71
Catalonia	*328*	*Mean*	494.70	487.65	504.03	*773*	*Mean*	475.84	466.89	480.54
		Std. Dev.	77.83	85.96	79.19		*Std. Dev.*	82.92	87.10	88.49
Galicia	*296*	*Mean*	509.77	506.36	526.14	*1,084*	*Mean*	489.44	471.99	499.05
		Std. Dev.	84.40	88.87	85.80		*Std. Dev.*	81.30	88.82	86.44
Navarre	*605*	*Mean*	537.67	496.09	529.99	*877*	*Mean*	504.36	468.12	498.07
		Std. Dev.	85.32	71.94	85.03		*Std. Dev.*	89.71	82.37	88.99
Rioja	*563*	*Mean*	532.31	505.82	529.48	*676*	*Mean*	523.92	486.02	517.30
		Std. Dev.	81.73	79.09	81.64		*Std. Dev.*	89.52	82.07	88.80
Basque	*2,255*	*Mean*	515.76	502.93	509.02	*1,541*	*Mean*	487.00	473.56	481.16
Country		*Std. Dev.*	78.67	80.90	79.92		*Std. Dev.*	87.37	92.28	84.28
TOTAL	***6,172***	***Mean***	***512.41***	***493.27***	***517.78***	***9,651***	***Mean***	***496.64***	***470.99***	***499.37***
		Std. Dev.	***82.00***	***80.80***	***81.87***		***Std. Dev.***	***86.34***	***85.02***	***86.21***

Source: *PISA* 2006 Report for Spain

As table 4 shows *GDPS* schools perform better than public ones, so the average students' performance is higher for the first ones in all disciplines and regions, where average scores for total Spain are around 512.41 on mathematics, 493.27 on reading and 517.78 on science. Moreover students from La Rioja or Navarre (Andalusia) present the highest (smallest) average result in all disciplines in both school types, although student's result is better on mathematics in all regions.

Table 5 presents a brief description of each variable.

Table 5: Variable definitions

VARIABLE	*DESCRIPTION*
Outputs	
MATH	students' results on Mathematics (5 plausible values)
READING	students' results on Reading (5 plausible values)
SCIENCE	students' results on Science (5 plausible values)
Control variables for the propensity score matching analysis	
PARED	Highest parental education in years
HISEI	Highest parental occupational status
IMMIGRANT	The student and/or parents' students was/were born abroad (1 = yes; 0 = no)
CITY	School community (1 = city or large city; 0 = town, small town or village)
SCHOOL	Attending to a private-voucher school (1 = yes; 0 = no)
Inputs for the parametric distance function approach	
SCMATEDU	Index of the quality of the school's educational resources
ESCS	Index of economic, social and cultural status
PEER	Average ESCS index of the student's peer group
PCGIRLS	Proportion of girls in the class
REPEAT ONCE	The student has repeated once (1 = yes; 0 = no)
REPEAT MORE	The student has repeated more than once (1 = yes; 0 = no)
STRATIO	Weighted number of teachers divided by total number of students
SCHLSIZE	Number of students in school
FIRSTMGEN	The student and at least one of the parents was born abroad (1 = yes; 0 = no)
SECGEN	The student was born in Spain but at least one of the parents was not (1 = yes; 0 = no)
GENDER	The student gender (1 = girl; 0 = boy)

4. EMPIRICAL ANALYSIS

In this section, we present the main results obtained in our analysis. Firstly, we report the unbiased impact of attending to a *GDPS* school across regions (*ATT*). Secondly, *ATTpf* and *ATTpfe* are presented after taking into account all relevant educational inputs and the mean efficiency in each school type respectively.

4.1. Average Treatment Effect on the Treated

Table 6 shows the mean *ATT* in *PISA* score and, for comparability purposes, we also present the *ATT* in standard deviation for each region with respect to average total Spain *PISA* score. A positive (negative) difference implies that in mean *GDPS* (public) school students perform better than their public (*GDPS*) counterparts. In order to avoid bias problems in the final results, 15 *ATT* estimations for each region are calculated[25], one for each plausible value and discipline, although for the sake of simplicity we only report the average values.

The greatest mean impact of attending to a *GDPS* is observed in Navarre, where students present the highest significant and positive *ATT* in all disciplines, being the mean

[25] First stage matching estimations for each region are available in the Appendix.

differential around 22 points in *PISA* score and 0.26 standard deviations from average total Spain *PISA* scores. A similar effect is observed for students from Catalonia or Basque Country where all parameters are positive and significant. On the other hand, the significant superiority of public school students from Cantabria on mathematics should be highlighted, where non-treated students perform 10 points in *PISA* score and 0.12 standard deviations from average total Spain *PISA* scores higher than treated ones. Secondly, we observe that the average impact of attending to *GDPS* is higher (lower) on reading (mathematics) in all regions and on the other hand there is an important variability in this effect among regions and disciplines.

Table 6: ATT in PISA score and in standard deviation across Regions

	Obs	*Mathematics*			*Reading*			*Science*		
Region	*N*	*ATT*	*ATT(st-dev)*	*t-value*	*ATT*	*ATT(st-dev)*	*t-value*	*ATT*	*ATT(st-dev)*	*t-value*
Andalusia	1,393	2.16	0.03	0.43	8.52	0.11	1.71	-7.59	-0.09	-1.42
Aragon	1,376	4.33	0.05	0.74	9.87	0.11	1.89	6.50	0.07	1.42
Asturias	1,316	-4.81	-0.05	-1.00	12.71	0.15	2.46	7.32	0.08	1.50
Cantabria	1,383	-10.10	-0.12	-2.15	-3.52	-0.04	-0.72	-4.51	-0.05	-1.03
Castile-Leon	1,360	0.99	0.01	0.15	18.11	0.21	3.25	0.65	0.00	0.11
Catalonia	1,101	16.49	0.19	2.88	16.12	0.19	2.54	18.42	0.21	3.25
Galicia	1,380	4.89	0.06	0.87	23.26	0.28	4.01	13.42	0.16	2.29
Navarre	1,483	21.28	0.25	3.99	22.83	0.27	4.74	22.70	0.26	3.81
Rioja	1,239	-5.39	-0.07	-1.06	8.25	0.10	1.77	-2.44	-0.03	-0.46
Basque Country	3,797	17.67	0.20	5.64	15.72	0.18	5.08	17.25	0.20	5.48

4.2. Average Treatment Effect on the Treated on the production frontier

Results presented in section 4.1 show a better performance of *GDPS* students in all regions, with the exception of the significant *ATT* on mathematics in Cantabria. However, this approach does not take into account all essential aspects in the educational production function, such as the socioeconomic background of students, the peer-group effect or school variables as the proportion of girls in the class or the student-teacher ratio. So we estimate five output distance functions, one for each trio of plausible values, for both school types in each region[26].

Output parameters are all of them positive which it means that the efficiency increases when, *ceteris paribus*, the performance in these subjects improve. The opposite effect happens with the main input coefficients, which are generally negative and significant in all regional estimations. These results implies that an input expansion suppose a reduction in the student efficiency performance keeping the output vector fixed. We also observe that the impact of socioeconomic background on achievements in all disciplines is generally higher for public

[26] One hundred distance functions were estimated, although for the sake of simplicity these tables do not appear in this paper, but all of them are available under request to the authors.

schools across regions. From both, *GDPS* and public school, distance function estimations in each region we may obtain the measurement of *ATTpf*. This one allows us to analyze the average impact[27] of attending to a *GDPS* after considering all educational inputs and placing each student on its own production frontier. Table 7 reports *ATTpf* in *PISA* score and in standard deviations from average total Spain *PISA* scores for each discipline[28].

Table 7: ATTpf in PISA score and in standard deviation across Regions

	Obs	*Mathematics*			Reading			Science		
Region	*N*	*ATTpf*	*ATTpf (sd-dev)*	*t-value*	*ATTpf*	*ATTpf (sd-dev)*	*t-value*	*ATTpf*	*ATTpf (sd-dev)*	*t-value*
Andalusia	1,393	14.88	0.17	6.50	14.27	0.17	7.47	15.23	0.18	6.72
Aragon	1,376	1.68	0.02	0.45	1.58	0.02	0.45	1.69	0.02	0.45
Asturias	1,316	17.56	0.20	2.70	16.85	0.20	2.70	17.94	0.21	2.79
Cantabria	1,383	7.30	0.08	3.30	6.89	0.08	3.50	7.41	0.09	3.36
Castile-Leon	1,360	35.65	0.41	8.14	33.17	0.39	8.33	36.09	0.42	8.51
Catalonia	1,101	26.12	0.30	5.62	25.56	0.30	5.38	26.42	0.30	5.68
Galicia	1,380	31.39	0.36	7.06	30.17	0.35	6.98	32.07	0.37	7.07
Navarre	1,483	77.76	0.89	4.15	72.56	0.85	4.16	77.34	0.89	4.12
Rioja	1,239	3.71	0.04	1.02	3.56	0.04	1.13	3.93	0.05	1.13
Basque Country	3,797	35.12	0.40	22.55	34.35	0.40	23.34	34.73	0.40	23.54

Figures from table 7 show an even more widely predominance of *GDPS* on academic achievement in all disciplines after all educational determinants are considered. Hence, once educational inputs and full efficiency are taking into account, *GDPS* students perform better than their public counterparts in all regions and subjects. Thus, this advantage is around 0.88 (0.40) standard deviations from average total Spain *PISA* scores in Navarre (Castile-Leon and Basque Country). We also observe a higher variability of the school type impact across regions, which differ from 0.86 standard deviations from average *PISA* scores between students from Aragon and Navarre to 0.47 between students from Castile-Leon and Navarre, being these differences 0.33 and 0.06 using *ATT* measure.

4.3. Average Treatment Effect on the Treated on the production frontier assuming efficiency

[27] The *ATTpf* and *ATTpfe* are calculated under the hypothesis of all dummy inputs take value zero and the average value otherwise.

[28] For each distance function estimation three predicted values are obtained: mathematics, reading and science.

The last step of our procedure is to correct the *ATTpf* measurement across regions in order to allow for school types divergences in student performance once the efficiency component is taken into account. Table 8 reports *ATTpfe* in *PISA* scores and in standard deviations. Firstly, we observe an increment of the *GDPS* impact with respect to *ATT* after allowing for different efficiency behaviors among both school types, although there is not a specific pattern respecting to *ATTpf*. Secondly, some regions present a higher impact of attending to *GDPS* using *ATTpfe* with respect to *ATTpf*, such as Andalusia, Aragon, Catalonia and Basque Country. Hence, *GDPS* students are relatively more efficient that public ones in these last regions. In contrast to this, in Asturias, Cantabria, Castile-Leon, Galicia, Navarre and La Rioja the *ATTpf* values are higher than *ATTpfe* are. These last results indicate the performance of public school students in those regions improve using *ATTpfe*, which suggests there are some divergences in student efficiency between both school types across regions. Consequently, *GDPS* students from Andalusia, Catalonia and Basque Country, whose process of decentralization in education was twenty years before, seem to be more efficient than ones in other regions where the decentralization was later.

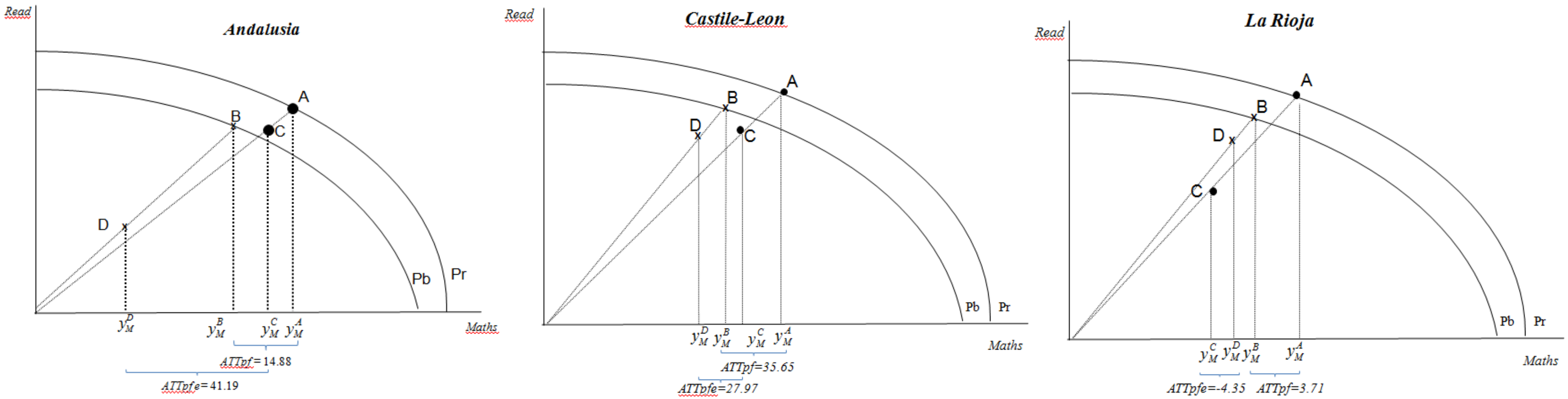
On the other hand, La Rioja is the only region where public school students perform better than *GDPS*, with an average improvement of 0.05 standard deviations from average *PISA* scores. It is worth to highlight here that whereas the average impact of attending to *GDPS* is positive on the production frontier (*ATTpf*=3.71), this value turns negative considering mean student efficiency divergences in both school types (*ATTpfe*= -4.36). In other words, in this region the best option is to attend to the most efficient *GDPS* however assuming mean inefficiency behaviors in the learning process the second best would be a public school.

Table 8: ATTpfe in PISA score and in standard deviation across Regions

	Obs	*Mathematics*			Reading			Science		
Region	*N*	*ATTpfe*	*ATTpfe (sd-dev)*	*t-value*	*ATTpfe*	*ATTpfe (sd-dev)*	*t-value*	*ATTpfe*	*ATTpfe (sd-dev)*	*t-value*
Andalusia	1,393	41.19	0.47	3.81	39.46	0.46	3.68	42.16	0.49	3.76
Aragon	1,376	22.50	0.26	17.16	21.18	0.25	18.91	22.61	0.26	17.26
Asturias	1,316	11.64	0.13	7.04	11.17	0.13	7.04	11.89	0.14	7.72
Cantabria	1,383	3.10	0.04	3.28	2.92	0.03	3.75	3.14	0.04	3.45
Castile-Leon	1,360	27.97	0.32	18.67	26.03	0.31	17.98	28.32	0.33	16.42
Catalonia	1,101	32.84	0.38	17.42	32.13	0.38	15.97	33.21	0.38	18.36
Galicia	1,380	29.95	0.34	15.15	28.77	0.34	14.47	30.59	0.35	15.16
Navarre	1,483	62.84	0.72	35.22	58.23	0.68	38.79	62.01	0.72	43.09
Rioja	1,239	-4.36	-0.05	-2.77	-4.08	-0.05	-2.68	-4.32	-0.05	-2.80
Basque Country	3,797	46.88	0.54	100.43	45.53	0.53	96.10	46.28	0.53	130.58

Figure 2 shows three different examples of *ATTpf* and *ATTpfe* for Andalusia, Castile-Leon and La Rioja respectively. As we can see *GDPS* frontier (*Pr*) is always above the public one (*Pb*), which implies a better technology transforming educational inputs into academic attainments. The first graph (Andalusia) represents the situation where the mean student's result between both school types is higher using *ATTpfe* that *ATTpf*. This indicates once taken into account the mean student efficiency in both school types *GDPS* students' perform even better than public ones. In Castile-Leon the situation is similar however when mean student efficiency is considered the gap between both school types reduces from 35.65 to 27.97 pointing out that public schools are on average more efficient than *GDPS*. Last, the only case where the difference in favor of *GDPS* using *ATTpf* reverse to public school advantage when considering *ATTpfe*. This situation seems to indicate that although best schools are *GDPS* this group on average is more inefficient than their public counterparts.

Figure 2. Some ATTpf and ATTpfe examples for Andalusia, Castile-Leon and La Rioja.



5. CONCLUSIONS

In this paper, we propose an original approach in order to compare students' achievements and efficiency divergences among both publicly financed school types. Firstly, we use propensity score matching (*PSM*) in order to obtain unbiased students comparisons among school types. This technique allows us to match treated students with their counterfactuals to guarantee we compare homogeneous groups. Secondly, we analyze through a stochastic distance function educational differences by school type from *PSM* sample. Thirdly, the implementation of both methodologies simultaneously allows us to enhance the conclusions obtained after calculating the Average Treatment of the Treated on the Production Frontier (*ATTpf*) and the Average Treatment of the Treated on the Production Frontier assuming Efficiency (*ATTpfe*).

Following this aim two different output distance functions were estimated from public and *GDPS* from *PSM* subsample in each Spanish region. The results seem to reflect divergences in student efficiency in both school types across regions. Hence, we observe that *GDPS* students perform better than public ones in Catalonia, Navarre and Basque Country, whose decentralization in education was in the early eighties. This results seem to indicate that the own mechanisms and organization in these *GDPS* are more adequate than the ones in other regions. On the other hand, students from La Rioja benefit more from public schools, so it is the only region where public school students perform better than *GDPS*. So, these regions are an example of both educational organization and management that other regions should follow in order to guarantee the same educational opportunities and the equity in the learning process to avoid that students' performance depend on the school choice or the region of residence.

To summarize we do believe that the conceptual framework presented in this paper, based on joint use of PSM and distance function at the student level, together with the two new measurements for reflecting school type differences provide an appealing methodology for policy makers in order to benchmark the best educational practices, avoiding unfair comparisons between the GDPS and the public systems. However, similar analysis must been developed continuously in the time to evaluate the evolution in both the students' achievements and the school management just to ensure the equity in the Spanish educational system and with the purpose of improving the efficiency always it would be possible.

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APENDIX

Table1: Mean Logit regression

REGION	*Obs*	*Variables*	*cons*	*Pared*	*Hisei*	*Immigrant*	*City*
		Coeff	-2.373	0.098		-2.527	0.723
Andalusia	1,419	*Std.Dev.*	0.184	0.015		1.022	0.129
		Prob	0.000	0.000		0.013	0.000
		Coeff	-1.924	0.054		-1.421	1.031
Aragon	1,376	*Std.Dev.*	0.215	0.016		0.347	0.126
		Prob	0.000	0.001		0.000	0.000
		Coeff	-1.738	0.061		-0.586	0.233
Asturias	1,318	*Std.Dev.*	0.229	0.018		0.460	0.127
		Prob	0.000	0.001		0.203	0.066
		Coeff	-1.519	0.049		-0.165	1.102
Cantabria	1,385	*Std.Dev.*	0.213	0.017		0.316	0.126
		Prob	0.000	0.004		0.601	0.000
		Coeff	-1.830		0.023	0.018	0.253
Castille-Leon	1,369	*Std.Dev.*	0.172		0.003	0.358	0.123
		Prob	0.000		0.000	0.960	0.040
		Coeff	-2.011	0.048		-0.995	1.382
Catalonia	1,149	*Std.Dev.*	0.229	0.018		0.259	0.139
		Prob	0.000	0.007		0.000	0.000
		Coeff	-2.550	0.083		-0.372	1.165
Galicia	1,381	*Std.Dev.*	0.227	0.019		0.444	0.148
		Prob	0.000	0.000		0.403	0.000
		Coeff	-2.326	0.109		-0.586	1.418
Navarre	1,489	*Std.Dev.*	0.214	0.016		0.249	0.116
		Prob	0.000	0.000		0.019	0.000
		Coeff	-1.678	0.083		-1.137	1.087
La Rioja	1,240	*Std.Dev.*	0.214	0.017		0.293	0.123
		Prob	0.000	0.000		0.000	0.000
		Coeff	-0.122		0.008	-1.561	0.515
Basque Country	3,797	*Std.Dev.*	0.099		0.002	0.202	0.071
		Prob	0.218		0.000	0.000	0.000