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LA EDUCACIÓN SECUNDARIA EN ESPAÑA: UN ANÁLISIS DE EFICIENCIA CON APROXIMACIONES ALTERNATIVAS

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“Nunca consideres el estudio como una obligación,
sino como una oportunidad para penetrar en el bello
y maravilloso mundo del saber”
(Albert Einstein)

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Eva

Contenido

INTRODUCCIÓN

La educación constituye uno de los programas fundamentales que dan contenido al Estado del Bienestar característico de las sociedades occidentales avanzadas. A su importancia cuantitativa en los presupuestos de las Administraciones Públicas añade una mayor relevancia por su contribución a los dos objetivos básicos de la Economía Pública, la eficiencia y la equidad.

El análisis de los resultados del sistema educativo se ha visto impulsado por la proliferación, en las últimas décadas, de evaluaciones tanto nacionales, por ejemplo el NAEP (*National Assessment of Educational Progress)* en Estados Unidos, como internacionales, entre las que destacan TIMSS (*Trends in International Mathematics and Science Study*), IALS (*International Assessment of Literacy Survey*), PIRLS (*Progress in International Reading Literacy Study*) y, especialmente, PISA (*Programme for International Student Assessment*).

El interés de la OCDE por evaluar el rendimiento académico en distintas materias de los alumnos que finalizan la escolaridad obligatoria (quince años) de manera comparada entre algunos de sus países miembros y otros asociados[1], ha dado lugar a los conocidos informes PISA. La publicación de sus resultados tiene en todos los países una notable repercusión política que, en el caso de España, se ve acentuada por la modesta posición relativa que alcanza, inferior a la media de OCDE y superada por la mayoría de los países de la Unión Europea.

Como el informe PISA es la base de datos que utilizamos en las partes aplicadas de la investigación parece conveniente que en esta introducción hagamos una descripción y valoración de ella aunque sea breve y general teniendo en cuenta que los aspectos específicos serán tratados en cada uno de los capítulos en función de sus objetivos concretos.

Los informes PISA se llevan a cabo cada tres años; comenzaron en el año 2000 y el último está previsto realizarlo en el 2015. Para hacer posible la comparación, las pruebas no se centran en contenidos curriculares sino en el dominio de procesos, en la comprensión de conceptos y en la capacidad para desenvolverse en distintas situaciones.

Una cuestión importante es la posibilidad que ofrece la base de datos de que las regiones participen con una muestra específica ampliada permitiendo con ello su comparación con otras regiones o países. Esa opción ha sido cada vez más utilizada por las CCAA españolas

[1] El total de países participantes fue de 32 en 2000, 41 en 2003, 57 en 2006 y 65 en 2009 (33 pertenecientes a la OCDE y 32 asociados).

pasando de tres evaluadas en 2003 a catorce en 2009[2] y es muy interesante para países como el nuestro donde las CCAA tienen asignada la gestión de las políticas educativas. Contar con información desagregada a nivel regional por una parte y por otra tener descentralizada buena parte de la política educativa a ese nivel, hace no solo posible sino conveniente y relevante incorporar la dimensión regional al análisis como hacemos en esta tesis.

El *output* educativo en PISA está representado por el resultado obtenido por los alumnos en una prueba de conocimientos estandarizada en lectura, matemáticas y ciencias (con una atención especial de una de las materias en cada oleada). Se trata de un *output* multidimensional ampliamente respaldado por la literatura especializada (*Fleischhauer,* 2007) aunque también es cierto que deja fuera la dimensión no cognitiva del proceso educativo (valores afectivos, comportamiento personal, desarrollo social, etcétera) mucho más difícil de medir. Un aspecto interesante es que al alumno se le asignan varias puntuaciones (concretamente cinco valores plausibles) extraídas aleatoriamente de la distribución de resultados en los que se tiene en cuenta errores de medida derivados de factores fuera de su control al realizar las pruebas. El indicador resultante utiliza como media de la OCDE un valor de 500 (con una desviación estándar de 100) y seis niveles de puntuaciones que facilitan la comparación e interpretación de los resultados.

En relación a los *inputs* educativos, hay dos cuestiones muy relevantes que merecen ser señaladas de la base PISA. Por un lado, la información que proporciona sobre las características socioeconómicas de los estudiantes, un factor destacado por la literatura por su relevancia en los resultados del proceso educativo. Por otro, al ofrecer una información desagregada al nivel de los alumnos, no solo permite mejorar las estimaciones al eliminar los problemas de agregación en unidades superiores (escuelas, por ejemplo) (*Summers y Wolfe* 1977; *Hanushek* 1997) sino también considerar, de forma simultánea e independiente, el nivel socioeconómico del alumno del de los compañeros (efecto compañeros), otro de los factores destacados en la literatura por sus consecuencias sobre los resultados académicos.

Las características socioeconómicas de los estudiantes se consiguen a partir de la información obtenida de un cuestionario que contestan los propios alumnos en el que, entre otros, se ofrecen datos sobre el bienestar económico del hogar, el nivel educativo y la cualificación profesional de los padres. Con ellos PISA construye un índice sintético

[2] En el año 2003 fueron Castilla y León, Cataluña y el País Vasco; en el 2006, Andalucía, Asturias, Aragón, Cantabria, Galicia, La Rioja y Navarra se unieron a las anteriores; en 2009 fueron 14 CCAA, ya que a las del 2006 se sumaron Baleares, Canarias, Madrid, Murcia y las ciudades autónomas de Ceuta y Melilla.

representativo del estatus social, económico y cultural (*ESCS*)[3]. En cuanto al efecto compañeros, éste puede medirse a partir del valor medio del índice *ESCS* del colegio en el que estudia el alumno cuyo rendimiento es evaluado.

Por el contrario, la información relativa a los *inputs* escolares tradicionales es bastante deficiente e inexistente la correspondiente a las condiciones innatas del alumno. Una de las partes del cuestionario que rellenan los directores de los centros, incluye información acerca de los recursos humanos y materiales de los que dispone el centro, la cual se utiliza para la construcción del índice *SCMATEDU* a partir de una serie de ítems (ordenadores disponibles, calidad de las infraestructuras físicas del colegio, recursos educativos, etc.). La principal limitación de esta información es que procede de las opiniones de los directores de los centros y no de observaciones externas, lo que dificulta su utilización como indicadores representativos de los recursos escolares.

De los mencionados cuestionarios se obtiene también información sobre variables de control que, sin ser factores productivos, pueden afectar al rendimiento educativo o a la mayor o menor eficiencia del mismo; algunas relativas a los estudiantes, como sucede con la condición de inmigrante o el sexo, otras correspondientes al centro, como ocurre con su titularidad o la disciplina en el aula[4].

Por último, señalar que, aunque las muestras son, lógicamente, representativas, los resultados no son estrictamente comparables en el tiempo (no coinciden alumnos y escuelas en las muestras de las distintas oleadas), lo que constituye otra limitación. Sería interesante, y más coherente con el carácter acumulativo del proceso educativo, poder contar con datos longitudinales donde la evaluación se realizara a lo largo del tiempo y el *output* fuera el valor añadido de la escuela.

En esta tesis doctoral utilizaremos la base de datos PISA no solo para identificar los factores asociados con los resultados del proceso educativo sino que, dando un paso más, tratamos de estimar y analizar la eficiencia del mismo. Identificar el comportamiento de algunas unidades como eficiente implica suponer que el resto no lo son e interrogarse por las causas de

[3] *ESCS* es un indicador construido a partir de tres variables: el nivel educativo más alto de cualquiera de los padres, el nivel más alto de ocupación laboral de cualquiera de los dos padres y un índice de posesiones educativas relacionadas con la economía del hogar, entre los que se incluyen los siguientes: lugar de estudio, habitación propia, ordenador para tareas escolares, software educativo, conexión a internet, calculadora, libros de literatura, libros de poesía, trabajos de arte, libros de ayuda educativa, diccionario y lavavajillas.

[4] No todas las variables se mantienen en las distintas oleadas del Informe como sucede, por ejemplo, con la disciplina en el aula que no aparece en 2006.

la ineficiencia en el ámbito educativo. Una explicación general sería la falta de esfuerzo y motivación de los agentes involucrados en el proceso educativo (alumnos, profesores, padres, etcétera) derivados de problemas de organización institucional (incentivos y coordinación de sus acciones).

En definitiva, esta tesis se compone de tres trabajos sobre la eficiencia de la educación secundaria en España que utilizan la base de datos PISA y presta una especial atención a la dimensión regional. A continuación describimos brevemente los objetivos y contenidos de cada uno de ellos.

En el primer capítulo se estima la eficiencia educativa mediante una función distancia paramétrica. Se trata de una técnica novedosa, escasamente aplicada, utilizada por *Perelman y Santín* (2011a, 2011b) en el ámbito educativo y que, a pesar de su carácter paramétrico, se adapta a ese ámbito ya que combina una relativa flexibilidad con la posibilidad de aplicación a procesos *multi-output multi-input*. A diferencia de los trabajos anteriores que estiman la frontera productiva educativa clásica (*Batesse y Coelli* 1988), en este capítulo se sigue, de forma original en la literatura educativa, el modelo de *Battese y Coelli* (1995). La utilización de esta aproximación permite, además de contrastar la existencia de una relación adecuada entre los *inputs* y los *outputs* anteriormente descritos de la base de datos PISA (2006), la posible asociación entre la eficiencia estimada y una serie de variables de control que proporciona la base de datos como son la condición de inmigrante, repetidor, el tamaño del aula, la titularidad del centro o la procedencia regional.

En el segundo capítulo se va más allá de la simple asociación de variables y se procede a analizar los mecanismos causales subyacentes. Para ello se combina la aplicación de una técnica de inferencia causal cuasi-experimental, el Propensity Score Matching (PSM), con la anteriormente comentada función distancia para estimar la eficiencia. Con la aplicación conjunta de ambas técnicas, algo totalmente novedoso en el ámbito educativo, evitamos el sesgo de selección en el que se incurre al comparar la eficiencia entre centros públicos y concertados derivado de la capacidad de discriminación que tienen los últimos en función de las características personales y familiares de los alumnos. El análisis por CC.AA. sirve para comprobar la existencia de diferencias en los resultados derivados del componente regional. En este capítulo se proponen además, por primera vez, nuevas medidas para evaluar el impacto de la titularidad educativa comparando además del impacto promedio entre dos grupos, el impacto promedio asumiendo que los individuos están en la frontera y el impacto promedio asumiendo que todos los individuos tienen la eficiencia media de su grupo.

En el tercer y último capítulo consideramos como unidad de análisis la escuela y estimamos la eficiencia mediante una técnica no paramétrica, el Análisis Envolvente de Datos (DEA), tratando de superar una de las limitaciones señaladas de la base de datos PISA, la comparación de resultados en el tiempo. Con esa finalidad adaptamos el Índice de Malmquist calculando otro similar que denominamos Índice de Malmquist Educativo que permite comparar el promedio de productividad entre las escuelas públicas y concertadas, a partir del pseudo-panel que ofrece PISA, en el espacio (para varias CC.AA.) y en el tiempo (oleadas 2003, 2006 y 2009 de PISA). Además, teniendo en cuenta el carácter determinístico de la aproximación utilizada, adaptamos la metodología propuesta por *Simar y Wilson* (1999) con el fin de obtener intervalos de confianza de los Índices de Malmquist y de sus distintos componentes.

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CAPÍTULO 1

"Exploring educational efficiency divergences across Spanish regions in PISA 2006"

1. INTRODUCTION

One of the main goals in the field of economics of education is to define the relationship between school inputs, student background and achievements at school. However, after five decades of research, evidences found are still not solid enough; especially regarding the role of school inputs (*Cohn and Geske* 1990; *Hedges et al.* 1994; *Hanushek* 1997, 2003). This fact implies a serious drawback for policy-makers taking decisions about the allocation of public resources devoted to enhance the accumulation of human quality in their countries.

We actually know is that education is a high complex process with variables such as organization or non-monetary inputs implied in production (*Vandenberghe* 1999). It makes extraordinarily difficult to define a general educational production function that accurately includes all relevant factors in the educational production. Furthermore, it should be taken into account that there may be inefficient behaviors in the learning process due to multiple reasons such as the way in which resources are organized and managed, the motivation of the agents involved in this process or the structure itself of the educational system (*Nechyva* 2000; *Woessman* 2001).

In order to tackle the efficiency issue in education, many studies use deterministic nonparametric data envelopment analysis in empirical evaluations. Pioneer studies applying data envelopment analysis in education originate with *Bessent and Bessent* (1980), *Charnes, Cooper, and Rhodes* (1981) and *Bessent et al.* (1982)[5]. Other studies have considered parametric methodologies, mainly using the Cobb–Douglas specifications, but also the translog functional form proposed by *Christensen, Jorgenson and Lau* (1971). These studies have included *Jiménez* (1986), *Callan and Santerre* (1990), *Gyimah-Brempong and Gyapong* (1992), *Deller and Rudnicki* (1993), *Grosskopf et al.* (1997) and *Perelman and Santín* (2008). The main advantage of the parametric translog function is its highly flexible nature, which allows the study of second order interactions in the production process as well as the output-input partial derivatives. Nevertheless it is worth noting that most of the applied work developed around this issue is conducted using school as Decision Making Unit (DMU). However, *Summers and Wolfe* (1977), *Figlio* (1999) considered student-level data in their econometric studies; both concluded that the student unit is more appropriate than higher levels of aggregation. Their findings show that school inputs matter but their impact on different types of student varies considerably. In addition to this, *Hanushek, Rivkin and Taylor* (1996) conclude that the

[5] For an empirical survey of frontier efficiency techniques in education, see *Worthington* (2001).

econometric estimation of the educational production function data aggregation at school, district or even country level implies an upwards bias of estimated school resource effects.

In this paper we propose the use of a parametric stochastic distance function at student level. Under this specification, we explicitly consider that education is a process in which students use their own characteristics and the school inputs in order to transform them into academic results, subject to inefficient behaviors that can be identified at both student and school levels. Moreover, parametric stochastic distance functions allow dealing simultaneously with multiple outputs (e.g. math, reading and science test scores) and multiple inputs (including school inputs, student background and peer-group characteristics) within a stochastic framework. We adopt here a translog specification to estimate the parametric stochastic distance function at the student level. This allows us to calculate several aspects of the educational technology, mainly output elasticities with respect to inputs and outputs. Moreover we propose *Battese and Coelli* (1995) methodology to find out what are the main driven factors for explaining the educational inefficiency.

In order to illustrate the potentialities of the approach proposed here, we provide an application to Spanish educational data from the Programme for International Student Assessment (PISA), implemented in 2006 by the Organization for Economic Cooperation and Development (OECD). Through this initiative, the cognitive skills of students around the world are measured with the aim of identifying potential causes of school failure and serving as a basis for educational policy. The study was first developed in 2000 and it has been carried out periodically every three years with a regular increase in the number of participating schools and countries. PISA 2006 data base comprises information about over 400,000 students, belonging to 57 countries from which 30 countries belong to OECD and another 27 were not associated.

This database includes a wide variety of the students' background information collected by individual questionnaires. Most of this information refers to students' family background and learning strategies. In addition, the study also conducted interviews among the principals of the respective schools in order to collect information on the school resources, the number of teachers in the school, the responsibility regarding school relevant decisions or the principles of selecting students and so on (for an extensive review see OECD, 2007 and 2009).

This great volume of data offers an exciting framework to analyze and identify the potential influence of those different variables on results. Although we restrict our analysis to the Spanish case in 2006, so ten Spanish regions decided to take part in evaluation with an extended representative sample of their population. Furthermore, the decision about the quantity of the educational budget and its allocation in Spain is full competency of the regions. Hence, this analysis allows evaluating potential efficiency divergences among regions within the same country.

As we mentioned before, the possibility of using information at student level for measuring efficiency involves a great advantage regarding most of the studies completed within the educational context (*Waldo* 2007), which usually use aggregate data at country (*Alfonso and St. Aubyn* 2006), district (*McCarty and Yaisawarng* 1993; *Banker et al.* 2004) or school level (*Muñiz* 2002; *Cordero et al*. 2008). In addition, to facilitate the analysis and interpretation of estimated results (*Summers and Wolfe* 1977; *Hanushek et al.* 1996), this allows providing information of the students' efficiency independently of either educational system or school efficiency. Furthermore, the measurement of efficiency at student level allows considering separately student's own socioeconomic level and their schoolmates one (the so-called peer-group effect), two inputs which cannot be simultaneously included with aggregated data (*Santín* 2006).

The paper is organized as follows. Section 2 provides an overview of educational production functions and presents the parametric stochastic distance function and our estimation strategy. In Section 3 data set and variables selected are described. Section 4 provides results and a discussion of our empirical analysis and the final section offers some conclusions.

2. EDUCATION AND EFFICIENCY MEASUREMENT WITH A PARAMETRIC DISTANCE FUNCTION

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

The attempts to estimate educational production functions are based on the analogy between this sector and an industry. In the latter, the firms produce different outputs using inputs such as labor and capital which are transformed according to the existing technology into commodities and/or services. In education, schools produce educational outputs in the form of students' achievements and other valued results using facilities, equipments, teachers, students' own characteristics, peer-group interactions, supervisors and administrators. This relationship can be defined with a basic formulation expressed on the following way (*Levin* 1974; *Hanushek* 1986):

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

where Y_{is} represents the achievement of student *i* at school *s*, usually represented by standardized tests' results. 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 or infrastructures in the school, the influence of classmates or the peer-group effect (P_{is}), and the students' innate abilities (I_{is}).

This function can be estimated statistically using a multivariate regression model. A further refinement of the educational production function would be to construct a frontier production function where only those units that maximize their results according to their resources are placed within the boundary. In this case, instead of using simple econometric analysis to estimate the Equation (1), more sophisticated methods are required. Following *Perelman and Santín* (2008), we use parametric stochastic distance functions at student level in this paper in order to go beyond in the analysis of the educational production function. For this purpose, Equation (1) becomes:

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

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[6] in the population and to influence individual performance in a multiplicative way. This simple transformation places the empirical estimation of Equation (2) within the framework of parametric stochastic frontier analysis, which, under specific distributional assumptions, allows disentangling educational inputs, random effects and efficiency (distance to the production frontier).

2.2. *The parametric stochastic distance function*

Defining a vector of inputs $x = (x_1, x_2, ..., x_K) \in \Re^{K+}$ and a vector of outputs $y = (y_1, y_2, ..., y_M) \in \Re^{M+}$, a feasible multi-input multi-output production technology can be defined using the output possibility set $P(x)$, which represent the set of all outputs, $y \in \Re_{+}^{M}$, that can be produced using the input vector, $x \in \Re_{+}^{M}$. That is,

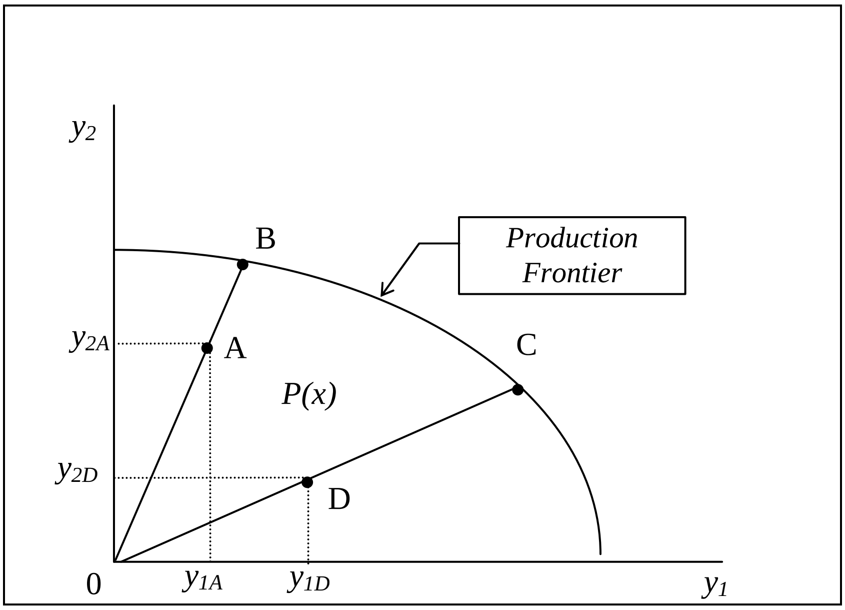
[6] The scoring of modern IQ tests such as the Wechsler Adult Intelligence Scale [Wechsler, 2008], the primary clinical instrument used to measure adult and adolescent intelligence, is now based on a projection of the subject's measured rank on the normal distribution with a central value (average IQ)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

$P(x) = \{(x, y) : x\, can\, produce\, y\}$ and we assume that the technology satisfies the set of microeconomic axioms listed in *Fare and Primont* (1995) including strong disposability, convexity, closedness and boundedness.

In order to capture efficiency behaviors, the output distance function, introduced by *Shephard* (1970), can be defined in the output set, $P(x)$, as $D_o(x, y) = \min\{\theta : \theta > 0, (x, y/\theta) \in P(x)\}$. As noted in *Fare and Primont* (1995), $D_o(x, y)$ is non-decreasing, positively linearly homogeneous and convex in *y* and non-increasing and quasi-convex in x. The distance function, $D_o(x, y)$, will take a value that is less or equal to one if the output vector, *y,* is an element of the feasible production set, $P(x)$. Then, if $D_o(x, y) \leq 1$ the mix (x, y) belongs to the production set $P(x)$ and only when $D_o(x, y) = 1$ the output vector, *y,* is located on the boundary of the output possibility set[7].

Figure 1 illustrates these concepts in a simple two-output one input setting. Let assume that DMUs *A*, *B*, *C* and *D* dispose of equal input endowment to produce outputs y_1 and y_2. Then *B* and *C* are efficient because both lies on the boundary of the output possibility set, whereas *D* and *A*, as interior points, are inefficient. The measurement of the relative inefficiency for *A* and *D* is given by the distance function $\theta_A = OA/OB$ and $\theta_D = OD/OC$.

Figure 1: Output possibility set P(X)



Source: Own compilation

[7] The distance function may be specified with either input or output orientation. So input distance function analysis could be defined in a similar way imposing an input orientation and given output endowments.

Our analysis focuses on the output distance function in order to evaluate the behavior of a group of students seeking to achieve the best possible academic results. More in depth, the definition of the distance function in the educational context is how the achievement vector may be proportionally increased subject to a fixed input vector.

We assume a *translog* functional form in our study to estimate the distance function with some properties such as flexibility, or homogeneity of degree +1[8]. This form has been used previously in other studies such as *Lovell et al.* (1994), *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:

$$\ln D_{ois}(x,y) = \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mis} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn} \ln y_{mis} \ln y_{nis} + \sum_{k=1}^{K} \beta_k \ln x_{kis} +$$
$$\frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} \ln x_{kis} \ln x_{lis} + \sum_{k=1}^{K}\sum_{m=1}^{M} \gamma_{km} \ln x_{kis} \ln y_{mis}$$
$$(i = 1,2,\ldots,N),\ (s = 1,2,\ldots,H) \qquad (3)$$

where sub-index *i* denotes the *i-th* pupil in the sample belonging to the *s-th* school, *K* is the total number of inputs and *M* the total number of outputs. With the aim of obtaining the frontier surface, we set $D_o(x,y)=1$, which implies that $\ln D_o(x,y)=0$. Furthermore, the parameters of the above distance function must satisfy some restrictions of symmetry

$$\alpha_{mn} = \alpha_{nm};\ m, n = 1, 2,\ldots, M,$$
$$\beta_{kl} = \beta_{lk};\ k, l = 1, 2,\ldots, K,$$

and homogeneity of degree +1 in outputs[9]. The analytical expressions of those restrictions are:

$$\sum_{m=1}^{M} \alpha_m = 1\ ; \quad \sum_{m=1}^{M} \alpha_{mn} = 0 \quad \text{and} \quad \sum_{m=1}^{M} \gamma_{km} = 0 \qquad (4)$$

[8] The Cobb Douglas form does not satisfy the concave imposition in the output dimension.
[9] The homogeneity restriction implies that the distance of the unit to the boundary of the production set is measured by radial expansion.

Then, in order to impose the homogeneity of degree + 1 in outputs, we normalize the output distance function arbitrarily by one output according to *Lovell et al.* (1994) and the expression may be expressed as follows:

$$\ln D_{ois}(x,y)/\ln y_{Mis} = TL(x_{is}, y_{is}/y_{Mis}, \alpha, \beta, \gamma) \tag{5}$$

where:

$$TL(x_{is}, y_{is}/y_{Mis}, \alpha, \beta, \gamma) = \alpha_0 + \sum_{m=1}^{M-1} \alpha_m \ln(y_{mis}/y_{Mis}) + \frac{1}{2}\sum_{m=1}^{M-1}\sum_{n=1}^{M-1} \alpha_{mn} \ln(y_{mis}/y_{Mis})\ln(y_{nis}/y_{Mis}) +$$

$$+\sum_{k=1}^{K} \beta_k \ln x_{kis} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} \ln x_{kis} \ln x_{lis} + \sum_{k=1}^{K}\sum_{m=1}^{M-1} \gamma_{km} \ln x_{kis} \ln(y_{mis}/y_{Mis}) \tag{6}$$

Rearranging some terms, the function above can be rewritten as follows:

$$-\ln(y_{Mis}) = TL(x_{is}, y_{is}/y_{Mis}, \alpha, \beta, \gamma) - \ln D_{ois}(x,y) \tag{7}$$

Following *Lovell et al.* (1994) we may consider the unobservable term $-\ln D_{ois}(x,y)$ as a random error term, which is the radial distance from the boundary. Then we can easily obtain the *Battese and Coelli* (1988) expression of the traditional stochastic frontier model proposed by *Aigner, Lovell and Smith* (1977) and *Meeusen and van den Broeck* (1977) considering $u_{is} = -\ln D_{ois}(x,y)$ and adding another term v_{is} capturing for noise:

$$-\ln(y_{Mis}) = TL(x_{is}, y_{is}/y_{Mis}, \alpha, \beta, \gamma) + \varepsilon_{is} \quad (\varepsilon_{is} = u_{is} + v_{is}) \tag{8}$$

Notice that the term $u_{is} = -\ln D_{ois}(x,y)$ is a non-negative random term assumed to be distributed as a semi-normal $\left|N(0,\sigma_u^2)\right|$ distribution and the term v_{is} is assumed to be a two-sided random (stochastic) disturbance designated to account for statistical noise and distributed iid $v\sim N(0,\sigma_v^2)$. Both terms are independently distributed, $\sigma_{uv} = 0$.

In the context of education, three kinds of variables are considered: scores obtained by students in standardized tests (outputs), one vector of educational variables indispensable for achievement (inputs), whose effect on results must be positive, i.e., a greater endowment of any of these variables must have positive impact on results. Finally, a set of variables about which we need to know whether or not they have influence on educational process since it cannot be known a priori if their effect is positive, negative or inexistent (environmental variables).

Therefore, we opt for using the *Battese and Coelli* (1995) model who propose a stochastic frontier model in which the inefficiencies effects u_{is} are expressed as an explicit function of a vector of environmental variables $z = (z_1, z_2, ..., z_s) \in \Re^S$ where:

$$u_{is} = \delta_0 + z_{is}\delta \tag{9}$$

where δ is a vector of parameters that must be simultaneously estimated with the parameters included in Equation (8). To the best of our knowledge, this is the first time in the economics of education literature that the *Battese and Coelli* (1995) model is implemented at student level considering the three sets of educational variables named above. This model enables us to identify the sign of each environmental variable effect and its influence on students' efficiency independently of the inputs. We think this framework is appealing in terms of educational policy makers taking decisions in order to get a better distribution and organization of public resources.

2.3. *Variance decomposition*

Due to the purpose of this paper, our main concern is not only to obtain a pure efficiency score for each pupil, net of inputs and environmental variables, but to identify which can be the causes of detected efficiency: the school or the student efficiency. Most of empirical work concentrates on only one responsible for efficiency, school or student. Nevertheless, in the real life, it is doubtful to assume that efficiency is only caused by students (mean efficiency among schools would be exactly equal) or by schools (mean efficiency within schools would be equal and all efficiency variance would be explained by average efficiency among schools). In this paper, we follow *Perelman and Santín* (2008) to decompose student and school inefficiency. We are especially interested in disentangling the efficiency attributable to school management of educational resources, so this is a factor over which public sector can make interventions through education policy.

After the estimation of the *Battese and Coelli* (1995) model depicted above, the decomposition of estimated efficiency may be carried out through an analysis of variance of the term $\hat{\theta}_{is}$, where $\hat{\theta}_{is} = \hat{u}_{is} - u_{is}$. Following *Perelman and Santín* (2008), we assume average efficiency differences among schools are due to efficiency attributable to schools (between), while differences among students in the same school (within) are due to students' self efficiency[10]. Hence, the decomposition of efficiency variance can be done as follows through one way analysis of variance:

$$\hat{S}^2_{u_{is}} = \hat{S}^2_{u_s B} + \hat{S}^2_{u_i W} \tag{10}$$

Thus, efficiencies among schools ($\hat{S}^2_{u_s B}$) include teachers' characteristics and motivation, pedagogical methods employed, management strategies or relationship between parents and principals. On the other hand, efficiencies within school ($\hat{S}^2_{u_i W}$) are attributable to students' dedication and effort. We expect that efficiency is a mix of both components.

2.4. *Elasticity estimations*

One advantage of parametric distance function is that this technique allows calculating the output and input elasticities which give us relevant information about the effect of each input on each output. A peculiarity of translog distance functions is that elasticity value is different in each observed unit, thus it is necessary to obtain the elasticity for each point. As it is usual in educational studies we analyze the distance function elasticity with respect to inputs and outputs and the change rate between inputs and outputs. For these purposes we use the following expressions:

$$r_{D,x_k} = \frac{\partial D}{\partial x_k} = \frac{\partial \ln D(x,y)}{\partial \ln x_k} \frac{D(x,y)}{x_k} \; ; \quad r_{D,y_m} = \frac{\partial D}{\partial y_m} = \frac{\partial \ln D(x,y)}{\partial \ln y_m} \frac{D(x,y)}{y_m} \tag{11}$$

where positive values of r_{D,x_k} (r_{D,y_m}) indicate that an increase in the input (output) implies a higher inefficiency (efficiency).

[10] If the input and control variables depicted in Equations 8 and 9 control for the other determinants of achievement (mainly the student's background, school variables, peer group effect and other characteristics or environmental variables), then the remaining efficiency effect depends only on student and school. Hence, we implicitly assume that (after controlling for x_{is} and z_{is}) student's outcomes and efficiency are independent variables. However, it is worth noting that a possible selection bias could arise if students are not distributed over schools independently of their potential efficiencies. This possibility could happen if most efficient students' are concentrated in the most efficient schools or if most efficient schools could select the most efficient students. What we assume in this paper is that x_{is} and z_{is} variables influence y_{is} but they are independently distributed of u_{is}.

Expressions of partial elasticities between output "*m*" and input "*k*", which indicate the variation in output "*m*" level before an increase in the input "*k*" proportion, and the variation of an output "*n*" with respect to another one "*m*", which can be interpreted as the extent the output "*n*" changes before an increase in the output "*m*", are as follows:

$$s_{y_m,x_k} \equiv \frac{dy_m/y_m}{dx_k/x_k} = \frac{r_{D,x_k}}{r_{D,y_m}} = \frac{\beta_k + \sum_{k=1}^{K}\beta_{kl}\ln x_k + \sum_{m=1}^{M}\delta_{km}\ln y_m}{\alpha_m + \sum_{m=1}^{M}\alpha_{mn}\ln y_m + \sum_{k=1}^{K}\delta_{km}\ln x_l} \tag{12}$$

$$s_{y_m,y_n} \equiv \frac{dy_n/y_n}{dy_m/y_m} = -\frac{r_{D,y_m}}{r_{D,y_n}} = \frac{\alpha_m + \sum_{m=1}^{M}\alpha_{mn}\ln y_m + \sum_{k=1}^{K}\delta_{km}\ln x_k}{\alpha_n + \sum_{n=1}^{M}\alpha_{mn}\ln y_n + \sum_{k=1}^{K}\delta_{kn}\ln x_k} \tag{13}$$

A positive sign in Equation (12) means that an increase in input "*k*" produces another increase in output "*m*". The interpretation is the opposite for the case of a negative sign. While in Equation (13) a negative sign entails that an increase in output "*m*" produces a decrease in output "*n*", and the opposite interpretation in case of a positive sign.

3. ANALISYS OF SPANISH RESULTS IN PISA 2006

3.1. Data

In our empirical analysis, we use Spanish data from PISA 2006 which provides data from 15 year-old students belonging to ten regions with extended sample of their population[11] (Andalusia, Aragon, Asturias, Basque Country, Cantabria, Castile Leon, Catalonia, Galicia, Navarre and La Rioja) and a group of 'other regions' including the seven remaining Spanish regions. It is worth noting here, that the Spanish regions are actually fully responsible for the management of educational resources in Spain since 2000. Therefore, they should be the most interested ones in analyzing PISA results as a previous step for the application of more effective educational policies. To perform this analysis, we have data about 19,605 students and 685 schools distributed across eleven regions as shown in Table 1. Schools can be divided into three groups according to the type of ownership: public (financed from government), private

[11] Three regions took part in 2003 evaluation (Basque Country, Castile-Leon and Catalonia). *Perelman and Santín* (2008) also analyze Spanish data from PISA 2003 but they do not study regional differences in efficiency, which is very informative for the case of Spain, since the education funding is totally decentralized.

(government independent) and government dependent (private management and financed by the government).

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

Region	*Students*	*Schools*	*Public*	*Gov-Dependent*	*Private*
Andalusia	1,463	51	37	13	1
Aragon	1,526	51	31	16	4
Asturias	1,579	53	31	14	8
Basque Country	3,929	150	63	83	4
Cantabria	1,496	53	31	19	3
Castile-Leon	1,512	52	31	17	4
Catalonia	1,527	51	29	11	10
Galicia	1,573	53	36	11	6
La Rioja	1,333	45	22	20	3
Navarre	1,590	52	30	19	3
Remainder regions	2,077	74	44	20	10
Total	**19,605**	**685**	**385**	**243**	**57**

Source: Own compilation from PISA 2006

One of the main advantages of the PISA study is that it does not evaluate cognitive abilities or skills through using one single score but each student receives a score in each test within a continuous scale. In this way, PISA attempts to collect the effect of particular external conditioning factors affecting the students during the test. Furthermore, it also involves that measurement error in education is not independent from the position of the student in the distribution of results. Precisely, students with very low or high results have higher associated measurement errors and higher asymmetry in the error distribution.

Likewise, given that school factors, home and socioeconomic context play an important role in students' learning, PISA also collects an extensive dataset on these variables through two questionnaires: one completed by the students themselves and another one filled out by school principals. From these data, it is possible to extract a great amount of information referred to the main determining driven factors of educational performance represented by variables associated to familiar and educational environments as well as to school management and educational supply.

3.2. *Variables*

To perform efficiency analysis we use three sets of variables: outputs, inputs and environmental factors. As output indicators we use test scores as it is usual in most of studies in education. However, the selection of inputs and exogenous variables can be complex and, in some cases, eventually confusing. Given that the literature does not provide an explicit rule to discriminate between them, in this study we base our decision on the following criteria. First, input variables must fulfill the requirement of isotonicity (i.e., ceteris paribus, more input implies equal or higher level of output). Thus, the selected input variable should present a significant positive correlation with the output vector in addition to theoretical support in previous studies. Second, input variables should be objective measures of educational resources or subjective opinions that could be checked by an external auditor. Third and finally, categorical and binary variables that divide the sample into different subgroups are considered as environmental factors to explain efficiency ex-post.

Outputs and plausible values

The true output as result of an individual education is very difficult to measure empirically due to its inherent intangibility. 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. Unfortunately, it is really difficult to measure all of them. 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 science) as the vector of educational output. As it has already been mentioned above, PISA uses the concept of plausible values to measure the performance of students, since measures in these subjects have a wide margin of error due to the fact that the measuring concept is abstract and is subject to the special circumstances of students and their environment on the date of their exams. Moreover, questions about educational knowledge may have different levels of difficulties and the measuring error is dependent on the student’s position in the distribution of academic results. Therefore, students with very high result suffer higher measuring error and higher asymmetry in his distribution than those students with average result. For this reason PISA 2006 used measures based on Rasch model (*Rasch* 1960; *Wright and Masters* 1982), which uses plausible values instead of working with a particular average value for each student’s knowledge. These are random values obtained from the distribution function of results, estimated from the answers in each test. They can be interpreted as a representation of the ability range for each student[12] (*Wu and Adams* 2002).

Table 2 reports the average value and the standard deviation for each plausible value and discipline (math, reading comprehension and science) across regions. Plausible values in the three tests are used as outputs in the efficiency analysis. In order to achieve correct results and avoid bias estimations it is necessary to calculate five different efficiency measures for each trio of plausible values and take the average one afterwards, instead of using mean values to obtain one efficiency measure (OECD 2005).

It is worth noting here that the standard deviation in results offers additional information about the equity on the educational system. For example, although Castile-Leon and La Rioja are the top performers regions in Spain, it seems preferable from a public policy point of view the results in Castile-Leon, where the standard deviation is considerable lower than in La Rioja. According to this reasoning, we can conclude that the distribution of test scores is quite similar across all the Spanish regions. Thus, it may be assumed that in Spain there not exists a clear trade-off between high scores at cost of damaging equity.

Inputs

In order to carry out the distance function efficiency analysis we have used three different inputs that are directly involved with student learning (ESCS, SCMATEDU and PEER) together with a set of control variables. Table 3 presents a brief description of each variable and Table 4 reports the main descriptive statistics of inputs and environmental variables by regions.

[12] For a review of plausible values literature see *Mislevy et al.* (1992). For a concrete Studio of Rasch model and how obtain feasible values in PISA, see OECD (2005.).

Table 2: Plausible values in mathematics, reading and science

		Plausibles Values Maths					*Plausibles Values Read*					*Plausibles Values Science*				
Region	*Measure*	*Math_1*	*Math_2*	*Math_3*	*Math_4*	*Math_5*	*Read_1*	*Read_2*	*Read_3*	*Read_4*	*Read_5*	*Sci_1*	*Sci_2*	*Sci_3*	*Sci_4*	*Sci_5*
Andalusia	*Mean*	470.11	470.01	470.31	469.46	470.51	452.41	453.72	451.72	451.88	452.13	481.63	482.36	481.29	481.07	481.33
	Std.Dev	-83.41	-84.11	-84.88	-85.34	-84.77	-85.86	-84.33	-85.02	-86.19	-85.48	-87.13	-86.66	-87.39	-89.70	-87.83
Aragon	*Mean*	514.59	514.86	516.71	515.62	515.87	484.89	485.11	485.78	485.11	485.00	514.86	515.52	516.37	515.99	516.86
	Std.Dev	-97.05	-96.56	-96.03	-96.04	-96.28	-86.90	-86.91	-86.12	-86.23	-86.31	-87.60	-87.29	-87.79	-87.50	-87.64
Asturias	*Mean*	501.45	500.45	502.31	501.15	502.60	482.51	481.39	483.00	482.17	481.56	513.26	511.89	513.40	513.12	513.55
	Std.Dev	-80.75	-81.10	-80.81	-79.82	-81.83	-80.52	-81.75	-81.92	-83.02	-82.56	-81.08	-82.46	-82.55	-82.14	-83.66
Basque Country	*Mean*	504.31	504.97	503.85	503.27	504.80	491.18	491.01	490.12	490.65	491.75	497.62	498.22	497.38	497.34	498.32
	Std.Dev	-83.06	-83.72	-84.23	-84.80	-84.07	-86.08	-87.65	-87.34	-86.98	-87.25	-81.80	-83.17	-83.18	-83.64	-82.97
Cantabria	*Mean*	506.60	506.23	505.87	506.12	506.05	479.06	479.27	477.99	479.38	478.83	514.46	514.17	513.43	514.16	513.86
	Std.Dev	-84.34	-83.79	-85.22	-83.65	-85.23	-84.83	-83.78	-84.46	-83.99	-85.01	-84.05	-83.58	-84.26	-83.56	-85.35
Castile Leon	*Mean*	519.91	519.41	518.99	517.80	518.65	481.39	480.72	480.14	479.71	481.07	524.47	523.33	522.24	522.53	523.11
	Std.Dev	-81.21	-81.92	-81.36	-82.15	-81.59	-74.26	-75.13	-74.80	-76.38	-75.04	-78.12	-79.06	-79.30	-80.00	-79.42
Catalonia	*Mean*	488.91	489.77	491.50	489.65	490.16	478.56	480.16	480.46	480.36	479.40	493.71	494.60	496.02	494.47	495.33
	Std.Dev	-85.72	-85.80	-87.13	-85.82	-85.10	-88.98	-88.30	-90.31	-87.95	-88.09	-89.46	-88.23	-90.52	-87.97	-88.01
Galicia	*Mean*	496.52	496.70	496.50	496.75	496.13	482.18	482.38	482.27	482.05	482.08	506.45	507.37	507.29	507.17	507.26
	Std.Dev	-82.53	-82.19	-82.14	-82.75	-82.02	-88.84	-88.82	-88.39	-88.29	-87.76	-87.33	-85.90	-85.66	-86.59	-86.65
La Rioja	*Mean*	526.59	526.31	526.69	525.66	526.83	496.11	494.37	495.51	494.82	494.55	522.54	520.89	522.62	521.47	522.02
	Std.Dev	-87.02	-88.78	-84.97	-87.73	-87.13	-82.14	-80.48	-80.76	-81.79	-82.63	-87.25	-88.63	-85.40	-87.36	-88.06
Navarre	*Mean*	517.06	519.43	518.88	519.02	519.09	482.04	481.80	481.72	480.99	481.80	511.95	511.87	512.06	512.04	512.51
	Std.Dev	-88.38	-88.69	-88.80	-90.05	-90.96	-79.03	-78.48	-77.89	-80.59	-79.38	-87.41	-87.06	-88.33	-88.72	-89.62
Reminder Regions	*Mean*	479.38	480.15	480.18	478.83	481.32	462.30	462.40	462.21	461.30	461.85	490.69	491.18	490.69	489.26	491.70
	Std.Dev	-87.01	-86.86	-87.22	-87.71	-87.70	-85.30	-86.52	-85.26	-86.05	-85.44	-90.40	-90.66	-91.00	-91.34	-90.19
Total Spain	*Mean*	501.80	502.13	502.27	501.51	502.43	480.24	480.21	479.98	479.83	480.10	504.92	505.00	504.99	504.63	505.38
	Std.Dev	-86.74	-87.02	-87.04	-87.37	-87.30	-85.07	-85.21	-85.20	-85.55	-85.38	86.24	-86.37	-86.68	-86.99	-86.90

Source: Own compilation from PISA 2006

Table 3: Variable definitions

VARIABLE	DESCRIPTION
Inputs	
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
Z's	
PRIVATE	Attending private school (1 = yes; 0 = no)
GOVDEP	Attending government-dependent private school (1 = yes; 0 = no)
SCHSIZE	Number of students in school
STRATIO	Weighted number of teachers divided by total number of students
REPONCE	The student has repeated once (1 = yes; 0 = no)
REPMORE	The student has repeated more than once (1 = yes: 0 = no)
IMMIGRANT1	The student and at least one of the parents was born abroad
IMMIGRANT2	The student was born in Spain but at least one of the parents was not
REGIONS	Belong to one region (ten different dummy variables)

Source: Own compilation

The index on the school's educational resources (*Scmatedu*) represents B_{is} in Equation (2). This variable was computed on the basis of seven items measuring the school principal's perceptions of potential factors hindering instruction at school (science laboratory equipment, instructional materials, computers for instruction, internet connectivity, computer software for instruction, library materials and audio-visual resources). The items are inverted for scaling and so, more positive values on this index indicate higher levels of educational resources[13].

Escs reflects the socio-economic background of each student. It is an index of the 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. Finally, *Peer* incorporates information about classmates' characteristics of students[14]. This variable is defined by the average of *Escs* of students who belong to the same school of the evaluated individual.

In addition to inputs variables we have considered other factors related to the characteristics of schools and students may influence efficiency in education (z's variables). In particular, we have analyzed the effect of the following ones:

[13] This variable shows a significant and positive correlation with the three outputs.
[14] For a review of the effect of these variables over results see *Betts and Shkolnik* (2000) or *Hanushek et al.* (2001).

School ownership. This variable has been included in the analysis in order to test whether the public, government-dependent private or private schools have some influence over students' efficiency. Regarding this issue, in the literature we find evidence supporting the idea of better performance in private schools (*Chubb and Moe* 1990; *Sander* 1996; *Figlio and Stone* 1997; *Neal* 1997; *McEwan* 2001), while others do not find enough evidence to justify this superiority (*Witte* 1992; *Goldhaber* 1996; *Vandenberghe and Robin* 2004; *Mancebon and Muñiz* 2007). In our case, we include this information using public school as reference. According to this criterion, two dummy variables have been defined: *Private,* which equals one if the school is private and zero otherwise, and *Govdep*, which takes value one for government-dependent private schools and zero otherwise.

School size (*Schsize*): This variable indicates the total number of students in the 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 this factor does not affect the results (*Hanushek and Luque* 2003).

Classroom size (*Stratio*): This variable is a ratio between total number of students in the school (*Schsize*) and total number of teachers weighted on their dedication (part-time teachers contributes 0.5 and full-time teachers 1). This variable is usually considered a school input in efficiency analysis according to the results of some studies where a direct relationship is found between reduced groups and higher academic performance (*Card and Krueger* 1992; *Hoxby* 2000; *Krueger* 2003). However, other studies conclude that this variable is not significant (*Hanushek* 1997, 2003; *Pritchett and Filmer* 1999). Taking into account that the linear correlation between this variable and the output is, contrary to expectations, positive, we decide to consider this information as an environmental variable in the efficiency analysis, in order to avoid potential bias in estimation, instead of considering it as an input.

Immigrant condition. This factor, whose influence has received increasing attention in literature within the last years (*Gang and Zimmermann* 2000; *Entorf and Minoiu* 2005; *Cortes* 2006). It becomes especially interesting for Spain as a consequence of the huge growth undergone by immigrant population at school age during the last decade[15]. In view of this phenomenon, several studies have recently analyzed the influence of this factor on the Spanish students' results by using information provided by PISA database (*Calero and Escardibul* 2007; *Zinovyeva et al.* 2008). In our study, this factor has been included throughout two dummy

[15] 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.

variables (*Immigrant1* and *Immigrant2*) that allow identifying the first and second order (the student and his/her parents were born abroad and the student was born in Spain but at least one of the parents was born abroad) immigrant condition.

Repeat Once and *Repeat More* are two dummy variables that represent those students that have repeated once or more than one course, respectively. There is a vast literature about the effect of grade repetition on academic performance and self-steem with the majority of educational researchers concluding that it is negative (*Holmes* 1989; *Jimerson et al.* 2002). This phenomenon may be rather significant in the case of Spain, where the repetition rate is much higher than in other countries in the OECD[16]. Obviously, it is expected that being repeater implies lower efficiency indices, although our aim is to quantify this effect after controlling for the different inputs and the environmental factors considered.

Regions. In order to test whether there are significant differences across regions in terms of efficiency, ten different dummy variables are constructed (one for each region with representative sample), taking the value one if the student belongs to a particular region and zero otherwise. According to this criterion, each region is compared with the sample of students belonging to the remainder regions.

[16] In Spain, 40% of students have repeated a course at least once in 2006 (*Fuentes* 2009).

Table 4: Descriptive statistic of inputs and environmental variables

Region	Obs.	*Measure*	*Scematedu*	*Escs*	*Peer*	*Private (%)*	*Govdep (%)*	*Schsize*	*Stratio*	*Reponce*	*Repmore*	*Immig1*	*Immig2*
Andalusia		*Mean*	4.05	5.51	5.49	0.02	0.24	700.88	13.51	0.32	0.09	0.03	0.07
	1,463	*St. Dev.*	-1.01	-1.08	-0.55	-0.15	-0.43	-356.82	-4.06	-0.47	-0.29	-0.16	-0.26
Aragon		*Mean*	4.63	5.96	6.02	0.09	0.30	708.24	12.12	0.28	0.06	0.07	0.10
	1,526	*St. Dev.*	-0.89	-1.02	-0.48	-0.28	-0.46	-412.82	-3.95	-0.45	-0.25	-0.25	-0.29
Asturias		*Mean*	4.61	5.97	6.01	0.16	0.24	645.18	11.44	0.25	0.05	0.03	0.09
	1,579	*St. Dev.*	-0.92	-1.02	-0.55	-0.36	-0.43	-336.62	-4.60	-0.43	-0.22	-0.18	-0.29
Basque Country		*Mean*	4.52	6.06	6.11	0.02	0.58	784.88	11.99	0.18	0.04	0.05	0.08
	3,929	*St. Dev.*	-0.90	-0.98	-0.51	-0.14	-0.49	-518.17	-4.73	-0.39	-0.18	-0.21	-0.27
Cantabria		*Mean*	4.44	5.93	5.97	0.06	0.33	619.23	11.46	0.30	0.06	0.06	0.10
	1,496	*St. Dev.*	-0.82	-0.97	-0.45	-0.24	-0.47	-257.44	-4.64	-0.46	-0.23	-0.23	-0.30
Castile Leon		*Mean*	4.66	5.89	5.86	0.09	0.30	717.15	12.07	0.28	0.06	0.04	0.07
	1,512	*St. Dev.*	-0.95	-1.01	-0.47	-0.29	-0.46	-390.38	-3.94	-0.45	-0.23	-0.19	-0.25
Catalonia		*Mean*	4.68	5.91	5.94	0.23	0.22	636.09	12.35	0.24	0.03	0.10	0.15
	1,527	*St. Dev.*	-1.02	-1.05	-0.59	-0.42	-0.41	-283.75	-3.41	-0.43	-0.17	-0.30	-0.36
Galicia		*Mean*	4.22	5.75	5.77	0.11	0.19	517.31	10.49	0.28	0.10	0.05	0.11
	1,573	*St. Dev.*	-0.89	-1.05	-0.60	-0.32	-0.39	-261.76	-3.98	-0.45	-0.30	-0.22	-0.31
La Rioja		*Mean*	4.67	5.97	5.99	0.06	0.42	611.76	13.10	0.27	0.05	0.07	0.10
	1,333	*St. Dev.*	-0.86	-0.99	-0.45	-0.24	-0.49	-363.27	-4.46	-0.44	-0.21	-0.26	-0.30
Navarre		*Mean*	4.69	5.95	5.88	0.05	0.38	700.04	10.78	0.22	0.04	0.08	0.12
	1,590	*St. Dev.*	-0.91	-1.01	-0.52	-0.23	-0.49	-424.33	-3.58	-0.41	-0.19	-0.27	-0.33
Reminder Regions		*Mean*	4.44	5.89	5.92	0.14	0.30	764.63	13.36	0.29	0.06	0.09	0.16
	2,077	*St. Dev.*	-0.99	-1.08	-0.64	-0.35	-0.46	-344.37	-5.26	-0.45	-0.23	-0.29	-0.37
Total Spain		*Mean*	3.21	5.49	5.76	0.09	0.35	689.49	12.07	0.26	0.06	0.06	0.10
	19,605	*St. Dev.*	-0.12	-0.89	-0.37	-0.28	-0.48	-395.23	-4.45	-0.44	-0.23	-0.24	-0.30

Source: Own compilation from PISA 2006

4. RESULTS

In this section, we present the main results obtained in our analysis. We estimate five output distance function, one for each trio of plausible values, assuming a stochastic *translog* technology to measure students' efficiency in PISA 2006. To do that, the first step is to impose homogeneity condition by selecting students' performance in math (y_1) as the dependent variable and then the ratios (y_2/y_1) and (y_3/y_1) as explanatory variables instead of y_2 or y_3 (students' performance in reading and science, respectively)[17].

In order to facilitate the interpretation of parameters, the original variables are transformed into deviation to the mean values, so first order parameters should be interpreted as the partial elasticity at the average values. Table 5 shows the results after averaging the five estimations.

Therefore, mathematics, reading and science parameters are all of them positive which means that the efficiency increases when, ceteris paribus, the performance in these subjects improve. In contrast, the opposite effect happens for input coefficients, which are all negative and significant; indicating that an input expansion suppose a reduction in the student efficiency performance keeping the output vector fixed. For this estimation we consider the model without separability between inputs and outputs due to most of the input-output cross-products coefficients are statistically significant. The average efficiency, computed as $E[\exp(-u_i|\varepsilon)]$, equals 0.82, indicating the average student's efficiency in Spain. The inputs and environmental variables in the model explain around one half of total variance[18].

The results derived from the analysis with z's variables allow drawing some interesting conclusions. The first relevant idea is that the class size has not effect on estimated efficiency. In fact, we find a weak but 90%significant effect pointing out that more students per teacher provides better efficiency[19]. This result bears strong implications for the educational policies instrumented by many Spanish regional governments generally concerned about reducing class size in schools.

[17] Following *Lovell et al.* (1994) homogeneity of degree +1 may be imposed if one arbitrary output is chosen and set $w = 1/y_M$ one obtains $D_o(x, y/y_M) = D_o(x, y)/y_M$.

[18] To compute the goodness of fit in the model we follow *Coelli and Perelman* (2001).

[19] *Calero and Escardibul* (2007) also obtain this non expected result between class size and PISA tests scores.

Table 5: Average of the five parametric output distance function estimations

Variables	*Coeff*	*Std.Dev*	*t-ratio*	*Variables*	*Coeff*	*Std.Dev*	*t-ratio*
Intercept	**-0.1969**	0.004	-45.911	$(Lnx_2)(Lny_2)$	-0.0330	0.055	-0.607
Lny_1 *(mathematics)*	<u>*0.4219*</u>			$(Lnx_2)(Lny_3)$	**0.1710**	0.075	2.298
Lny_2 *(reading)*	**0.3014**	0.009	32.910	$(Lnx_3)(Lny_1)$	<u>*0.1159*</u>		
Lny_3 *(science)*	**0.2767**	0.012	22.583	$(Lnx_3)(Lny_2)$	**0.6005**	0.110	5.477
<u>***Outputs***</u>				$(Lnx_3)(Lny_3)$	**-0.7164**	0.142	-5.058
$(Lny_1)^2$	<u>*1.9146*</u>			<u>***z's variables***</u>			
$(Lny_2)^2$	**0.0995**	0.008	11.731	*Intercept*	**0.2269**	0.030	7.524
$(Lny_3)^2$	**1.1993**	0.046	25.955	*Reponce*	**0.2317**	0.007	31.748
$(Lny_1)(Lny_2)$	<u>*-0.4074*</u>			*Repmore*	**0.3738**	0.010	38.730
$(Lny_1)(Lny_3)$	<u>*-1.5072*</u>			*Govdep*	0.0123	0.009	1.399
$(Lny_2)(Lny_3)$	**0.3079**	0.028	9.104	*Private*	-0.0045	0.012	-0.373
<u>***Inputs***</u>				*Schsize (ln)*	**-0.0141**	0.005	-2.991
Lnx_1 *(Scmatedu)*	**-0.0100**	0.004	-2.235	*Immig1*	**0.0511**	0.011	4.741
Lnx_2 *(Escs)*	**-0.1265**	0.007	-19.391	*Immig2*	0.0086	0.009	0.943
Lnx_3 *(Peer)*	**-0.1169**	0.014	-8.253	*Stratio (ln)*	-0.0221	0.013	-1.747
$(Lnx_1)^2$	**0.0041**	0.002	2.287	*Andalusia*	-0.0136	0.010	-1.308
$(Lnx_2)^2$	**0.1008**	0.050	2.008	*Aragon*	**-0.0855**	0.011	-8.084
$(Lnx_3)^2$	-0.2709	0.205	-1.315	*Asturias*	**-0.0559**	0.010	-5.329
$(Lnx_1)(Lnx_2)$	-0.0072	0.012	-0.592	*Basque Country*	**-0.0185**	0.009	-2.131
$(Lnx_1)(Lnx_3)$	0.0013	0.026	0.049	*Cantabria*	**-0.0741**	0.011	-6.925
$(Lnx_2)(Lnx_3)$	0.0582	0.077	0.764	*Castile-Leon*	**-0.1017**	0.011	-9.399
<u>***Input-output***</u>				*Catalonia*	-0.0052	0.010	-0.505
$(Lnx_1)(Lny_1)$	<u>*-0.0082*</u>			*Galicia*	**-0.0901**	0.011	-8.471
$(Lnx_1)(Lny_2)$	-0.0229	0.016	-1.401	*Navarre*	**-0.0663**	0.011	-6.026
$(Lnx_1)(Lny_3)$	0.0311	0.024	1.286	*La Rioja*	**-0.1164**	0.012	-9.663
$(Lnx_2)(Lny_1)$	<u>*-0.1380*</u>						
Sigma-squared	**0.0256**	0.001	39.481	*Mean Eff.*	0.824		
Gamma	**0.7796**	0.011	71.657	*R2*	0.51		

Source: Own compilation from PISA 2006.
**Note: Underlined parameters are calculated by applying imposed homogeneity conditions*

The second evidence is that variables related to course repetition show a clear negative relationship with efficiency scores, even higher when the student has repeated more than one academic year[20]. This result is relevant from the viewpoint of educational policy, since it raises certain questions regarding decisions on the convenience of repetition policies and their conditioning factors. There are multiple school, family, and individual characteristics associated with an increased likelihood of grade retention. Thus, simply repeating a grade is unlikely to address the combination of factors that contribute to low achievement or socio-emotional

[20] *Eide and Showalter* (2001), *Corman* (2003) obtained similar results using data from the United States.

adjustment problems. Therefore, it seems to be more reasonable to focus on early intervention strategies, especially for students at risk of poor performance.

Thirdly, as we expected, the immigrant condition has a negative influence on efficiency scores, although this relationship is only significant for the first generation immigrants, being non-significant for the second-generation immigrants[21]. These results reveal the need to implement specific policies aimed at improving the academic performance of these students.

Fourthly, schools' ownership is not significant so do not contribute to explain the students' efficiency. In other words, once school, student and environmental variables are taken into account we cannot conclude that ownership matter for explaining differences in efficiency. And finally, the students from all regions (with the exception of Andalusia and Catalonia) perform better in terms of efficiency than the students belonging the sample of the remainder Spanish regions. From our point of view, there is no a clear pattern to explain these results. From year two thousand, the educational system in Spain is totally decentralized to the regional governments that decide, independently of the central government, the amount of resources devoted to education. As a matter of fact, efficiency analysis allows identifying the best performers in order to learn and apply their successful educational policies in other regions. Hence, it seems that Aragon, Castile-Leon, Galicia and La Rioja are the benchmark regions.

Once the results of the initial efficiency analysis and second stage analysis is carried out, we may step forward and calculate the percentage of student inefficiency directly attributable to their schools, after the effect of the exogenous variables is considered. For this purpose and following Equation 10 we complete a variance analysis of students' results which allows identifying differences in average students' efficiency who belong to different schools (between-school variance), which can be attributed to school managerial efficiency, and the variance among students belonging to the same school (within-school variance).

Results reported in Table 6 show that the most important proportion of inefficiency detected depends on the student. Thus the average school inefficiency is almost 13 percent, denoting that school quality is quite uniform in Spain. As we mention in section 2.2, it newly seems that Spain has a strong equality of educational opportunities in terms of school choice. This means that when parents face up to the choice of school for their children they should not expect high efficiency differences among the considered schools. However, some significant divergences among regions can be detected. Hence, whereas Andalusia, Cantabria or Galicia

[21] This result may be conditioned by the low number of observations that have the value of one in this variable, since in Spain there are few second order immigrant yet.

presents around 8.5 percent, the Basque Country has a school variance of 25 percent. The causes for this relatively high value for Basque Country can be found in higher levels of school choice and a current process of yardstick competition since the proportion of government-dependent private schools in that region is the highest in the country.

Table 6: Variance analysis

Region	*Number of Schools*	*Number of Students*	*Between (school)*	*Within (student)*	*F-test**
Andalusia	51	1,463	8.66	91.34	2.64
Aragon	51	1,526	11.48	88.52	3.81
Asturias	53	1,579	12.01	87.99	3.99
Basque Country	150	3,929	25.10	74.90	8.36
Cantabria	53	1,496	8.53	91.47	2.57
Castile-Leon	52	1,512	10.24	89.76	3.26
Catalonia	51	1,527	16.16	83.84	5.65
Galicia	53	1,537	8.57	91.43	2.73
La Rioja	45	1,333	13.34	86.66	4.50
Navarre	52	1,590	11.04	88.96	3.73
Reminder Regions	74	2,077	17.00	83.00	5.59
Average	685	19,605	12.92	87.08	

Source: Personal compilation based on PISA 2006 data for Spain
**All F-test present statistical signification at 99%.*

Finally, with regard to elasticity estimations, we only report inter-quartiles values for the sake of simplicity, since we have an elasticity value for each student as it is discussed in section 1.4. Table 7 reports the input-output elasticities.

Table 7: Ouput-input derivates[22]

	Math Inter-quartiles			*Reading Inter-quartiles*			*Science Inter-quartiles*		
	25%	*50%*	*75%*	*25%*	*50%*	*75%*	*25%*	*50%*	*75%*
Output with respect to inputs									
Scmatedu	0.0153	0.0213	0.0303	0.0229	0.0299	0.0397	0.0209	0.0313	0.0508
Escs	0.2338	0.2845	0.3976	0.3221	0.4216	0.5581	0.2636	0.4101	0.6845
Peer	0.1403	0.2689	0.44	0.2228	0.3784	0.5584	0.1897	0.3823	0.6811

Source: Own compilation from PISA 2006.

We observe that all the variables have a positive influence on scores, although it is slight in the case of the scholar resources (*Scmatedu*). Furthermore, the outputs-inputs variations are different depending on the discipline. On the one hand the average elasticity of the student's

[22] The interpretation of elasticities is referring to the mean values, since original variables were transformed in deviation to the mean values.

socio-economic background (*Escs*) on reading is 0.42, 0.28 on mathematics and 0.41 on science. Then, the average elasticity of the peer-group effect (*Peer*) on mathematics, reading and science is 0.2689, 0.3784 and 0.3823, respectively. Here newly arises that an educational policy to avoid the concentration of students with a low socioeconomic background can become more productive that investing more in educational resources.

5. CONCLUSIONS

In this paper we analyze the differences on Spanish students' results in PISA 2006 through an educational frontier framework. With this aim, we have implemented an efficiency analysis using data at student level and considering information about Spanish regions and schools ownership that participate in this study. To the best of our knowledge, this is the first paper that analyzes the results of Spanish students in PISA 2006 using individual data and the *Battese and Coelli* (1995) model.

Considering the uncertain environment around the educational production function, we apply a stochastic parametric distance function methodology in order to measure students' efficiency. Our results show that detected divergences among regions maintain even when information about socioeconomic background, quality of resources and peer effects are taken into account in the analysis.

Moreover, the influence of exogenous variables over the student's efficiency shows that the teacher-student ratio is not a significant variable for explaining it. This result entails strong implications for the educational policies instrumented by many Spanish regional governments generally concerned about reducing class size in schools. Moreover, the school type (private or government dependent private one) do not seem to have influence on results either, since after considering the socioeconomic characteristics of students attending to these schools they perform similar to public ones.

In contrast, students repeating courses or those who were born in a foreign country have worse results in terms of efficiency. These results reveal the need to implement specific policies aimed at improving the academic performance of these students, such as hiring support teachers, improving teachers' training to cater for diversity or strengthening the role of social workers when it comes to make parents aware of the importance of education. Likewise, the school size or belong to any region, with the exception of Andalusia, Catalonia and remaining Spain, have a positive effect on the results, being Castile-Leon and La Rioja the most efficient educational systems in Spain.

Furthermore, an important advantage of our study is the interpretation of the output - input elasticities. After carrying out this analysis, the results show that all output-output elasticities present negative signs, being mathematics the discipline that experiment a higher impact. Regarding the input-elasticities, we notice that school resources have an average effect on students' scores close to zero, while socio-economic background and peer-group effect have a positive and significant effect on scores. This result claims for a deep revision of the actual system of assigning students into public-financed schools which is strongly based on proximity to residence criteria.

Although these conclusions should be interpreted with caution, since they are referred to cross-sectional data from a single year, we consider that our results have relevant implications for regional educational policy, which seems to be focused on enhancing students' efforts in view of the scarce percentage of variance attributable to schools.

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CAPÍTULO 2

"Does the school ownership matter? An unbiased comparison through propensity score matching and parametric distance functions"

1. INTRODUCTION

One of the main goals in the field of the economics of education is to analyze the efficiency component in the learning processes. Technical inefficiency may be due to multiple factors, including the lack of motivation or effort in students and teachers, pedagogical issues, or the quality and experience of teachers. These factors may affect student's performance significantly and, therefore may indirectly influence educational efficiency. While several papers in the education literature have focused on the role of organizational structure on educational outcomes (*Nechyva* 2000; *Woessman* 2001), few papers have done so from an economic perspective.

Most of the previous educational literature attributes an advantage to government-dependent private schools (*GDPS)* over public schools (PS) in terms of educational outcomes based on the fact that market competition would force private schools to achieve a more efficient use of resources and to offer a higher standard of quality to their students (*Alchian* 1950; *Friedman and Friedman* 1981; *Chubb and Moe* 1990). The analysis of PISA 2006 may seem to confirm this finding because, on average, the academic performance of *GDPS* is higher than that of *PS* across different countries. However, in most of the educational systems, the distribution of students across publicly financed schools is not random, with a higher percentage of low income students attending *PS*. This implies that a simple mean comparison of the results would be flawed due to the selection of high-income students into *GDPS* and low-income students into *PS*.

Empirical studies that address this issue find no solid evidence regarding the superiority of either type of school. 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). Other papers find no statistical differences between both types of schools (*Goldhaber* 1996; *McEwan* 2001; *Mancebón et al.* 2010); and even others conclude that public education is significantly better compared to that of privately managed schools (*Kirjavainen and Loikkanen* 1998; *Newhouse and Beegle* 2006).

This paper contributes to the above literature by proposing a new method to estimate the impact of school ownership on students' efficiency that is free from selection concerns and by applying it to measure efficiency of Spanish Schools. Spain is a particularly interesting case to study this issue. Publicly financed Spanish schools receive their core funding from the government agencies. Publicly financed schools can be classified as either entirely public schools (*PS*) or as government-dependent private schools (*GDPS*)[23]. The difference lies on whether a public entity or a private agency, respectively, has capacity to make decisions concerning its management. *PS* are monitored and managed by a public education authority or agency. *GDPS* are ruled by a non-public organization[24], which means that their governing board is not elected by a government agency. Private schools are classified as *GDPS* if they receive more than 50% of their core funding from government agencies[25].

Most Spanish families choose whether to attend a *PS* or a *GDPS* based on their location, their ideology and their expectations regarding what type of school offers the best quality of education for their children. Some people believe that teachers' quality is higher[26] in *PS* because teachers in these schools have passed a competitive exam to enter the public school system, which may lead to a better overall academic achievement. On the other hand, teachers in public schools are automatically granted tenure once they pass the entrance exam, which leads some people to argue that teachers in public schools do not have clear incentives to improve their methodologies and practices once they enter the system. Privately managed schools do not have this problem and therefore some people think that they might be more efficient and flexible than public schools. The different expectations regarding which school offers a better quality of education would only be a concern if they are not randomly distributed across families, which is not likely to be the case among a wide group families.

However, other factors are less likely to be random. In particular, a potentially important driving factor of the selection of students from low socio-economic status and/or students from large families into *PS* is that *GDPS* are allowed to charge a *voluntary monthly fee* (ranging from 30 € to 200 € per month and child) to parents under the claim that public funding is not enough to cover the total costs or to offer some extra-curricular activities. The fee is not mandatory which means that is up to the parents to decide whether to pay it. The selection comes from the fact that it is likely that certain groups of families may not know that the fee is voluntary (for example some immigrant population) and may therefore perceive *GDPS* as more expensive, which leads them to send their children to *PS*. Hence, although similar students could be found in both types of schools, the variability of the student's background is likely to be wider for *PS*.

[23] The so-called '*Escuela Concertada*' in Spanish

[24] Most of these organizations include catholic schools, teachers' cooperatives, non for profit organizations or simply private enterprises.

[25] 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 the 50% of their core funding from the government agencies. Although in this paper, we focus only on the publicly financed schools.

[26] The requirements for teaching in *PS* or *GDPS* are different. Hence, to pass a hard state exam is required in the first one, while a three years university degree for the second one.

In this paper we propose an alternative methodology to measure educational efficiency that corrects the selection bias steaming from the school choice decision in Spain. The novelty of our approach lies in the use of a Propensity Score Matching (*PSM*) estimator within the framework of the stochastic frontier analysis. A similar approach[27] was implemented by *Mayen et al*. (2010) in order to compare the productivity and the efficiency between the organic and the conventional farms in Finland. To the best of our knowledge, however, the *PSM* and the stochastic frontier analysis have not been previously used jointly to assess school efficiency.

To carry out this task, we first use PSM to choose an unbiased sub-sample of schools in each of the ten Spanish regions with a representative sample in PISA 2006. We then estimate two stochastic parametric frontiers, one for each school type. The use of parametric distance functions presents some advantages for the estimation of educational production functions compared to other methods. Among these advantages is worth mentioning its higher flexibility, its stochastic character or the fact that allows us to calculate elasticities and to perform statistical inference. However, the efficiency measures may be biased if we do not correct for the problem of self-selection into *GDPS*. Although the use of PSM deals with the selection problem, the measurement of the impact of school ownership using only the PSM methodology does not correctly reflect the real difference in the students' achievements from both school types. Thus, we suggest combining both methodologies in order to obtain unbiased comparisons of students' efficiency. Moreover, we propose two original new concepts; the Average Treatment effect of the Treated on the Production Frontier (*ATTpf*) and the Average Treatment effect of the Treated assuming school inefficiency (*ATTasi*), which are more robust indicators of the impact of *GDPS* attendance in terms of technical efficiency.

The case of Spain is particularly relevant to study these issues due to the poor results that Spanish students achieved in *PISA* 2006 compared to other European countries [*Fuentes* 2009]. The bad overall performance of Spanish students has led to an intense political debate about which type of school is likely to produce better academic outcomes. In addition, education policies are greatly decentralized to the regions, which means that the regional governments decide the total amount of public funds allocated to education and its distribution. Moreover, there is a significant gap of almost twenty years among the regions whose decentralization process in education was in the early eighties -Andalusia, Basque Country, Catalonia, Galicia and Navarre- and those for which decentralization took place in the late nineties -Aragon, Asturias, Cantabria, Castile-Leon and La Rioja. The analysis of student's efficiency across regions allows also exploring the influence of the decentralization process on

[27] Another possible approach would be to combine stochastic frontier analysis and switching regression (*Greene* 2010).

the managerial experience and to check the possible regional divergences on the impact of the school ownership on academic achievement and educational efficiency.

The analysis is performed using the student as the decision making unit. Many studies that measure educational efficiency aggregate the decision making units at the country (*Alfonso and St. Aubyn* 2006), the district (*McCarty and Yaisawarng* 1993; *Banker et al.* 2004) or the school (*Muñiz* 2002) level. In this paper we prefer to use the student as the decision making unit because considering separately the student background and the scholar resources allows us to test the influence of school inputs on students' results (*Waldo* 2007).

The paper is organized as follows. Section 2 provides an overview of the distance function and the propensity score matching approaches and how our estimation strategy combines both of them. In Section 3, we describe the data set and the selected inputs and outputs from the Programme for International Student Assessment (*PISA*). Section 4 provides the results and a discussion of our empirical analysis. The final section summarizes the 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's achievement using their facilities and equipments, the teachers, the students' own characteristics, the peer-group interactions, the supervisors and the administrators. Following *Levin* (1974) and *Hanushek* (1979) this relationship can be defined as:

$$Y_{is} = f(B_{is}, S_{is}, P_{is}, I_{is}) \tag{1}$$

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

Other institutional factors may also influence the variation on students' results across schools. Some of these factors are, among others, the main pedagogical choices, the organizational structure, the incentive schemes or teachers' effort and motivation. All these variables are difficult to capture and are usually gathered into the efficiency component. Following *Perelman and Santín* (2011) we may estimate the educational multi-output and multi-input production frontier assuming inefficiency behaviors according to Equation (2):

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

where *g* represents the best practice technology used in the transformation of educational inputs into outputs and D_{is} is the distance that separates each student *i* attending school *s* from the technological boundary. The unobservable student innate abilities, I_{is}, are assumed to be randomly normally distributed among the population[28] of students and to influence the individual performance in a multiplicative way. From Equation (2) we may, first, identify the divergences in performance and efficiency attributed to students and, second, test the statistical importance of the main educational factors and the impact on students' attainment. For the empirical analysis, we propose a parametric distance function, which has been previously used in other studies such as *Grosskopf et al*. (1997) or *Coelli and Perelman* (1999, 2000).

A flexible *translog*[29] functional form is assumed to estimate the output oriented parametric distance function. Equation (3) shows the specification[30] for the case of *M* outputs and *K* inputs:

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

[28] 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.

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

[30] Distance function parameters must satisfy some restrictions as symmetry and homogeneity of degree +1 for outputs, which implies that the distance of the decision making unit to the boundary of the production set is measured by radial expansions.

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. In order to obtain the frontier surface, we set $D_o(x,y)=1$, which implies that $\ln D_o(x,y)=0$.

Following *Lovell et al*. (1994), normalizing the output distance function by one output is equivalent to imposing homogeneity of degree +1. Then, by rearranging terms, the expression of the traditional stochastic frontier model can be expressed through Equation (4):

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

where *TL*(•) denotes the *translog* functional form. 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 from the random noise term, v_i , which is independently and identically distributed as a normal distribution $N(0,\sigma_v^2)$.

The simple maximum likelihood estimation of Equation (4), by adding a dummy variable to identify differences in performance by school type may yield biased results given selection concerns, especially for the Spanish case. Preferences apart, students admission into *PS* or *GDPS* is based on a point system that is subject to different legal criteria across different regions. The main factors considered in the point system are household income, family size (three or more siblings), the closeness of the school to the student's residence and the number of siblings already attending the school. In addition, as mentioned in the introduction, low socio-economic families self-select themselves into *PS* because they cannot afford some of the voluntary extra-payments that are charged by most *GDPS*.

The ideal measurement of the true impact of the school ownership attendance on students' achievement would require observing the performance of the same student in both, *PS* and *GDPS*. However, it is only possible to observe the student's attainment in one school. To overcome this problem, a counterfactual[31] of each *GDPS* student (treated) must be sought among *PS* students (non-treated) through a 'quasi-experimental' evaluation technique.

As we mentioned in the introduction, a wide group of medium income families have a similar motivation to maximize the quality of their children' education, but they finally attend *PS* or *GDPS* for different reasons such as religious beliefs, ideology, the expected quality of

[31] A student attending a *PS* is counterfactual of a student from *GDPS* if both students have similar personal and family characteristics and, have a very similar *a priori* probability of attending *GDPS*.

teachers, the management flexibility, etc. Nevertheless, we observe a higher proportion of low socio-economic students in *PS*, who have not counterfactual in *GDPS*. Thus, we propose the use of the PSM technique in order to achieve a better comparison.

2.2. *The Propensity Score Matching*

The aim of PSM is to find a counterfactual, within a large group of non-treated students, closer to students in the treated group, conditioning on a set of observable variables, *Z*, that solve the selection bias[32] (*Rosembaum and Rubin* 1983; *Heckman and Navarro–Lozano* 2004). In order to implement it, we first estimate the probability of attending *GDPS* (propensity score) for each student through a logit analysis.

$$p(S_i) = \frac{\exp^{Z_i \cdot \gamma}}{1 + \exp^{Z_i \cdot \gamma}} + \xi \qquad (5)$$

where S_i equals one if the student attends *GDPS* and zero otherwise, $p(S_i)$ is the estimated probability of attending *GDPS*, Z_i is a set of observable characteristics that determines 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 treated students and their counterfactual. Then, from the matched subsample, the average impact of school ownership attendance is calculated through the Average Treatment effect on the Treated (*ATT*) as the difference of the average student's performance between both, *GDPS* and *PS*, controlling by the school choice variables as Equation (6) shows:

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

where $Y_i(1)$ and $Y_i(0)$ are the average achievements in both, *GDPS* and *PS*, respectively, supposing the two counterfactual situations of treatment (attending *GDPS*) and no treatment (attending *PS*). $P(S_i)$ is the probability of attending *GDPS* for the student *i*, conditioned to Z_i.

In order to achieve a proper implementation of the matching strategy, some properties are imposed, such as the *unconfoundedness*[33], which guarantees the independence between the

[32] We do think that in the Spanish educational context there are not other unobservable characteristics influencing the school choice and results.
[33] The unconfoundedness or Conditional Independence Assumption (CIA) implies: $Y(0), Y(1)\ II\ S\,|\,Z, \forall Z$.

outcome and the treatment effect, given *Z*, or *common support*, that forces the comparison only among very close individuals, given *Z.*[34]. For empirical purposes, the estimation problem due to a high dimensional vector *Z*, was solved by Rosenbaum and Rubin (1983) who demonstrated that matching may be performed conditioning on the propensity score *p(S),* instead of conditioning on the *Z* vector. Then, if the outcome is independent of the treatment received for a given set *Z*, it is also independent for a given *p(S).* Finally, both groups, treated and non-treated, must have the same distribution of observable and unobservable characteristics, which means that only very close individuals are compared.

2.3. Our strategy

We propose a new framework to analyze efficiency in education. Two alternative approaches are combined in order to achieve unbiased students' efficiency comparisons between different school types. Firstly, the PSM approach is implemented to obtain unbiased subsamples of treated and non-treated students for each Spanish region with representative sample in PISA 2006. Then, two production frontiers at the student level, one for each school type[35] and region, are estimated through the parametric distance function approach. Moreover, three measures are built with the aim of achieving the impact of the school ownership on the student's results.

Thus, our proposal consists of a three stage procedure. In a first step, we estimate the *ATT* that reflects the academic performance gap between both school types focusing only on the *GDPS* self selection. Secondly, we add other relevant educational factors involved in the learning process to the last measure in order to reflect differences in achievements between schools. We name it Average Treatment effect on Treated on the production frontier *(ATTpf).* Finally, with the aim of analyzing school inefficiency disparities, the third measure, Average Treatment effect on Treated assuming school inefficiency (*ATTasi)* is built from the main inputs information and the average school inefficiency.

Equation (7) reflects the *ATT* for each regional sample and discipline, using the nearest neighbor estimator[36] -the closest individual in the control group- to obtain the matched pairs:

[34] An extensive review about this issue may be found in *Caliendo and Kopeing* (2005)

[35] We assume different technologies, so the management drivers differ in both school types, while *GDPS* teachers are hired and fired by school principals and present a more flexible management, *PS* teachers need to pass a high difficult state exam and they cannot be fired. Our argument is confirmed later on Table 9 where inputs parameters are in general significantly different for *GDPS* and *PS* estimations.

[36] 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).

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

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 production frontiers, one for each regional matched-sample. We are assuming different technologies for each region and school type because educational policies are decentralized to this level, so the organization structure and the economic resources devoted to each school type are not necessary the same among different regions[37]. This procedure allows us to obtain a new measure, the Average Treatment effect on the Treated on the Production Frontier (*ATTpf*), as the difference of the average predicted output in the production frontier between both *GDPS* and *PS* by discipline and region.

$$ATT_{pf}^R = E\left[\hat{y}_{i,G}^R\right] - E\left[\hat{y}_{i,P}^R\right] \tag{8}$$

where sub-index G (P) refers to students attending *GDPS* (*PS*) and $\hat{y}_i^R$ is the average educational output vector for each production frontier and region. This measure captures the disparities in students' results between both school types, after considering all relevant inputs[38] involved in the learning process and assuming that students are fully efficient[39]. The computation of this measure starts by carrying out a radial projection of each student to its estimated production frontier. We then average the predicted performance for all students belonging to the same school type on their frontier. This measure allows selecting a group of students with relevant characteristics and only obtaining the *ATTpf* for this cluster of students[40].

Finally, in order to take into account the mean efficiency divergences among schools across disciplines and regions, we define the Average Treatment effect on the Treated assuming school inefficiency (*ATTasi)* as follows:

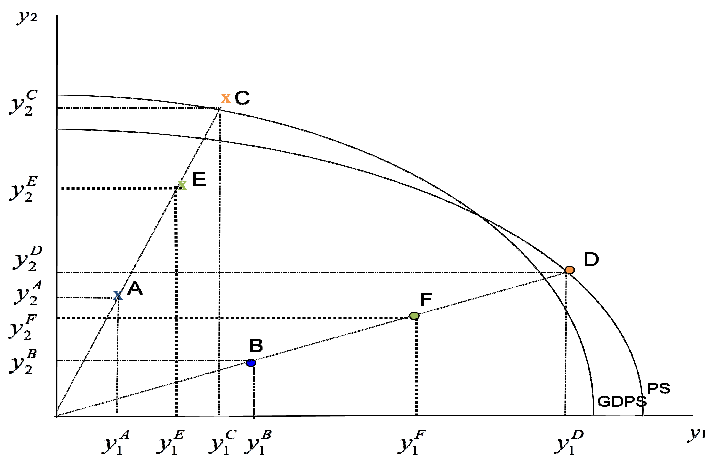
$$ATT_{asi}^R = \left\{E\left[\hat{y}_{i,G}^R\right]\cdot \bar{u}_G^R\right\} - \left\{\left[\hat{y}_{i,P}^R\right]\cdot \bar{u}_P^R\right\} \tag{9}$$

[37] Some divergences in the students' results can be explained by the regional context due to factors as the local economic development, the employment possibilities, the immigrant population, the rural areas extensions, the socioeconomic background of the population or the differences among their educational policies.
[38] Note that only school choice variables were considered for the *ATT* measurement.
[39] To do this we perform a radial projection of all students to the estimated production frontier.
[40] Thus, our methodology can provide a wide range of *ATTpf* and *ATTasi* measurements according to different students' typologies.

where $\overline{u}_G^R$ and $\overline{u}_P^R$ are the average estimated students' inefficiencies in both *GDPS* and *PS* in each region, respectively. Equation (9) represents the difference in achievements between *GDPS* and *PS*, controlling by *GDPS* self-selection and incorporating the main educational factors and the average school inefficiency for each school type.

Figure 1 illustrates these three measures in a simple two-output one equal input setting, where *GDPS* (*PS*) represents the *government-dependent private school* (*public school*) production frontier. Let assume that *A* and *B* are two different students, the treated and his/her counterfactual (non-treated) attending *GDPS* and *PS*, respectively. 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 the educational inputs, outputs and other factors that are involved in the educational production process, we may estimate the production frontiers for *GDPS* and *PS* as well as the technical efficiency for each student. The next step is to project both students, *A* and *B*, to their respective production frontiers (*C* and *D*), being the difference between the two outputs in dots *C* and *D* the *ATTpf* measure for outputs y_1 and y_2. Finally, by allowing for different average students' inefficiencies in both school types, the *ATTasi* is obtained as the difference between the outputs obtained in dots *E* and *F* for outputs y_1 and y_2.

Figure 1: ATT, ATTpf and ATTasi measures



Source: Own compilation

3. ANALISYS OF SPANISH EDUCATION IN PISA 2006

3.1. Data

In our empirical analysis, we use Spanish data from *PISA* 2006 Report which provides data from 15 years old students attending schools in one of the ten regions that decided to take part in the evaluation with an extended representative sample of their population (Andalusia, Aragon, Asturias, Basque Country Cantabria, Castile-Leon, Catalonia, Galicia, Navarre and La Rioja). 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 fully responsible for the management of educational resources. Therefore, this analysis is also worth for comparison purposes and as a source of information for more efficient educational policies and in order to guarantee equality of educational opportunities. The sample includes data from 15,918 students and 564 schools distributed across ten regions as shown in Table 1.

Table 1: Distribution of students by school ownership and region

Region	*Students*	*Number of PS*	*Number of 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: *Own compilation from PISA 2006 database.*

3.2. Variables

Control variables for the PSM analysis

The first step of our estimation procedure involves obtaining matched pairs of students through the PSM analysis[41]. In this stage, *School* is the dependent variable that reflects the treatment[42] and the set of covariates includes variables that are directly correlated with the parents' school ownership choice (*Pared, Hisei, Immigrant* and *City*).

Pared and *Hisei* represent the index scores for the highest educational[43] and occupational[44] level of parents, respectively. *Pared* is measured as estimated years of schooling

[41] As a consequence of imposing balancing property to ensure that only students with the same probability of attending *GDPS* are matched, the total sample size reduces from 15,918 to 15,123 students.
[42] PSM is generally calculated using *Pared, Immigrant* and *City* as control variables, with the exception of Basque Country and Castile-Leon where *Hisei* is used instead of *Pared* to impose the balancing property.
[43] Parental education (*Pared*) 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).
[44] *Hisei* is the higher level labor occupation of any of the student's parents according to the International Socio-Economic Index of Occupational Status (ISEI). For more details see *Ganzeboom et al*., (1992).

and *Hisei* reflects the highest occupational status of either of the parents. Our hypothesis is that the probability of attending *GDPS* increases with *Pared* and *Hisei*.

Immigrant status. This factor has received increasing attention in the literature in recent years (*Witte* 1998; *Gang and Zimmermann* 2000; *Entorf and Minoiu* 2005; *Cortes* 2006; *Schnepf* 2008). In the case of Spain this is an especially relevant covariate due to the growth of the immigrant population at school age during the last decade[45]. Several studies have recently analyzed the influence of this factor on the academic achievement of Spanish students using PISA data (*Chiswick and DebBurman* 2004; *Calero and Escardibul* 2007; *Zinovyeva et al.* 2008; *Calero and Waisgrais* 2009; *Mancebón et al*. 2010). A control for immigration status is included in both the PSM and the efficiency analysis through three different dummy variables. The one included in the PSM analysis is *Inmigrant* and takes value one when the student and/or his/her parents was/were born abroad and zero otherwise. Our hypothesis is that the probability of attending *GDPS* decreases when the student is an immigrant.

The community size is captured by the variable *City*, which takes value one if the community is a city of more than 100,000 inhabitants and zero if the school is located in a town, small town or village[46]. Following *Vandenberghe and Robin* (2004), who showed positive influence of household location on school choices, we consider it as a control variable for the *PSM* analysis (*McEwan* 2001; *Sander* 2001; *Perelman and Santín* 2011).

The dependent variable in the PSM analysis, *School* takes value one when the student attends *GDPS* and zero for *PS* attendance. As we remarked in the introduction of the paper, according to the literature, the expected influence of this variable on students' achievements is not clear.

Inputs for the parametric distance function approach

We use four different inputs for the distance function estimation described in Equation (3) (*Scmatedu, Escs, Peer and Pcgirls*)[47] jointly with seven control factors (*Repone, Repmore Schsize, Stratio, Firstgen, Secgen and Gender*) that do not interact with other variables in the *translog* production function. All of them are directly involved in the student learning process

[45] According to Spanish official educational 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.

[46] 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.

[47] We have considered that all the inputs variables are continuous and show significant positive correlations inside each school type and across all the regions. The remaining control variables are categorical variables (dummies) or do not fulfill in our database a clear significant positive correlation with output (*schsize*).

and are expected to have a positive influence on students' performance. Including the control variables in the educational production function allows us to analyze their impact over academic results.

Scmatedu[48] represents the quality of the school resources. This variable is an index derived from school principals' responses to seven items related to the availability of educational resources such as computer for didactic uses, educational software, calculators, books, audiovisual resources, and laboratory equipment. Previous research is inconclusive regarding the role of school resources on academic performance. While some studies show a positive influence (*Carroll* 1963; *Krueger* 1999), others find that there is no direct correlation between more school inputs and better academic outcomes (*Hanushek* 1986, 1997, 2003; *Cordero et al.* 2010a, 2010b).

Escs reflects the s*ocio-economic background* of each student. It is an index of student's economic, social and cultural status created by PISA analysts from three variables related to family background. The first variable is 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 second variable is the index of highest parental occupation status according to International Socio-economic index of Occupational Status (*ISEI*, *Ganzeboom et al*. 1992). The third variable is the index of educational possessions at home.

Peer incorporates information about the characteristics of students' classmates[49]. This variable is defined as the average of the *Escs* variable of students that share the same school as the evaluated one.

Pcgirls is an index of the proportion of girls at school that is based on the enrolment data provided by the schools' principals. It is computed by dividing the number of girls by the total number of students at the school. We introduce this variable in order to test if higher proportions of girls imply better academic results as it was found for Spain by *Calero and Escardibul* 2007; *Calero et al*. 2009 and *Salinas and Santín* 2012.

Repeat once (Repone) and *Repeat more (Repmore)* are two dummy variables that capture whether or not students have repeated one or more than one school year, respectively.

[48] Since positive and negative values can be found in the original variable, we have re-scaled all the values in order to have only positive values for the input variables.

[49] For a more detail review about the effect of these variables on students' results see *Betts and Shkolnik* (2000) or *Hanushek et al.* (2001).

This phenomenon is quite important in the case of Spain, where the repetition rate is much higher than in other countries from the OECD[50] (*Fuentes* 2009). Again, the effect of this variable on educational results is not clear. A few previous papers find a certain positive correlation (*Pierson and Connell* 1992; *Roederick et al.* 2002) between repetition rates and academic performance, but the majority of previous studies conclude that repetition leads to a reduction of academic performance and to a considerable increase in the probability of students' dropping out (*Holmes and Mathews* 1984; *Shepard et al.* 1996; *Alexander et al.* 2003).

School size (*Schsize*) indicates the total number of students in the school. The influence of this variable in the educational process has also been tested in previous studies. Some papers support that schools with more students have better results (*Bradley and Taylor* 1998; Barnett *et al.* 2002) while others find no influence of size on students' results (*Hanushek and Luque* 2003), and even others that lower school sizes reduce the dropout rate and the proportion of early school-leaving (*Mora et al.* 2010).

Classroom size (*Stratio*) is the teacher-student ratio. It is measured as the number of full-time equivalent teachers per a hundred of students. In the calculation of full-time equivalent teachers, part-time teachers contribute 0.5. This variable is usually considered as a school input in the educational efficiency analysis due to some studies that find a direct relationship between reduced class size, more labor resources devoted to education, and higher academic performance (*Card and Krueger* 1992; *Hoxby* 2000; *Krueger* 2003; *Mora et al.* 2010).

Firstgen indicates the immigrant origin. This variable takes value one when the student and at least one of his/her parents were born abroad. Similarly, *Secgen* denotes a student that was born in Spain but at least one of his/her parents was born abroad, which allows us to identify the first and second generation immigrants.

Gender takes value one for girls and zero for boys. 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 achieve higher results from PISA 2006.

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

[50] More than 40% of Spanish students have repeated a course almost once in 2006 (source PISA 2006).

Table 2: Descriptive statistics of matching GDPS schools inputs sample

Region	Obs	*Variable*	*Pared*	*Hisei*	*Immigrant*	*City*	*Scmatedu*	*Escs*	*Peer*	*Pcgirls*	*Repone*	*Repmore*	*Stratio*	*Schsize*	*Primgen*	*Secgen*	*Gender*
Andalusia	353	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
		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	451	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
		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	374	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
		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	489	Mean	12.419	46.103	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
		Std. Dev.	3.460	17.123	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 Leon	458	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
		Std. Dev.	3.551	17.286	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	328	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
		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	296	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
		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	605	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
		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	563	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
		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 Country	2255	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
		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	**6172.000**	***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: Own compilation from PISA 2006

Table 3: Descriptive statistics of matching public schools inputs sample

Region	Obs	*Variable*	*Pared*	*Hisei*	*Immigrant*	*City*	*Scmatedu*	*Escs*	*Peer*	*Pcgirls*	*Repone*	*Repmore*	*Stratio*	*Schsize*	*Primgen*	*Secgen*	*Gender*
Andalusia	1,039	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
		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	924	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
		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	941	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
		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	894	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
		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 Leon	902	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
		Std. Dev.	3.736	16.108	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	773	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
		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	1,084	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
		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	877	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
		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	676	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
		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 Country	1,541	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
		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: Own compilation from PISA 2006

the proportion of immigrant and repeater students or the quality of the scholar resources is usually higher, with the exception of Andalusia and Aragon, being the only regions where both, repeating several years and the quality of school resources, are higher for *GDPS*, respectively. As *GDPS* are privately managed they try to minimize all their costs which implies optimizing educational resources and maximizing the class sizes because more students imply more voluntary-fee incomes. Finally, it is worth mentioning these input differences among both school types are not so wide in Catalonia.

Outputs and plausible values

The educational output is very difficult to measure due to its inherent intangibility. Education does not consist only on the ability to repeat information and answer questions, but also involves the skills to interpret information and to learn how to behave in society. In spite of the multi-product nature of education, most studies have used as outputs the results obtained in cognitive tests since they are difficult to manipulate and respond to administration demands. But perhaps, as *Hoxby* (2000) states, the most important reason could be that both policy makers and parents use this criterion to evaluate the educational output.

In this study we use the test scores obtained by students in the three competences evaluated in *PISA* (mathematics, reading comprehension and science) 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 a dichotomous variable (PASS, NOT PASS), 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 students' performance, which corresponds with five random values from the students' results distribution in each discipline[51]. This approach let us to consider the wide margin of error in the measure of achievements due to the fact that these measures are abstract, complex and subject to the special circumstances of students and their environment on the date of their exams.

Table 4 reports the average plausible values[52] for the three tests (mathematics, reading comprehension and science) in both *PS* and *GDPS* after controlling the selection bias. Five different plausible values in the three tests are used as outputs in the *PSM* and the educational efficiency analysis respectively. In order to obtain unbiased results five different efficiency analysis for each trio of plausible values are estimated and afterwards averaged, instead of using

[51] 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 and estimations in *PISA*, see *OECD* (2005).
[52] From now on and for presentation purposes we only report the mean results of analyzing the five plausible values in each discipline.

mean values to obtain only one efficiency measure (*OECD* 2005). Similarly, five different *ATT* measures for each plausible value and region are calculated and averaged.

As Table 4 shows, *GDPS* outperform *PS*. The average of the students' performance is higher for *GDPS* in all disciplines and regions. It is also remarkable that, generally, standard deviations are higher for *PS* compared with their *GDPS* counterparts.

Table 4: Descriptive statistics of PSM outputs sample

			GDPS					*PS*		
	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: Own compilation from PISA 2006 database.

Table 5 summarizes all the information described above in Table 5.

Table 5: Variable definitions

VARIABLE	DESCRIPTION
Outputs	
MATH	Student's result on mathematics (5 plausible values)
READING	Student's result on reading (5 plausible values)
SCIENCE	Student's result 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 *GDPS* (1 = yes; 0 = no); Dependent variable in the logit model.
Inputs variables 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 school
Control variables for the parametric distance function approach	
REPONE	The student has repeated a school year (1 = yes; 0 = no)
REPMORE	The student has repeated more than one school year (1 = yes; 0 = no)
SCHLSIZE	Number of students in school
STRATIO	The weighted number of teachers per 100 students
FIRSTGEN	The student and at least one of the parents were 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, Table 6 shows the logit results. As expected, the variables related to the student's socioeconomic background are positive and significant in all regions, so we may conclude that the probability of attending *GDPS* increases when the family present less problems to afford the voluntary fee. Moreover, being an immigrant reduce significantly the probability of attending *GDPS* in Andalusia, Aragon, Basque Country, Catalonia, Navarre and Rioja. Finally, living in a city or big city is also highly related to the probability of attending *GDPS*, although in Asturias this relationship is only significant at the 90% level.

Table 6: Mean Logit regression

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

Source: Own compilation from PISA 2006 database.

Secondly, we report the traditional *ATT* measure of the impact of attending *GDPS* across regions. Then, the *ATTpf* and *ATTasi* are presented after taking into account all relevant educational inputs and the average school inefficiency in each school type, respectively.

4.1. Average Treatment Effect on the Treated

Table 7 shows the mean *ATT* in *PISA* score and we also report the *ATT* in standard deviation for each region referring to average total Spain *PISA* score. A positive (negative) difference implies that in average *GDPS* (*PS*) students perform better (worse) than their *PS* (*GDPS*) counterparts.

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

	Obs	*Mathematics*			*Reading*			*Science*		
Region	*N*	*ATT*	*ATT(Std.Dev)*	*t-value*	*ATT*	*ATT(Std.Dev)*	*t-value*	*ATT*	*ATT(Std.Dev)*	*t-value*
Andalusia	1393	2.16	0.03	0.43	8.52	0.11	1.71	-7.59	-0.09	-1.42
Aragon	1376	4.33	0.05	0.74	9.87	0.11	1.89	6.50	0.07	1.42
Asturias	1316	-4.81	-0.05	-1.00	***12.71***	***0.15***	2.46	7.32	0.08	1.50
Basque Country	3797	17.67	0.20	5.64	***15.72***	***0.18***	5.08	***17.25***	***0.20***	5.48
Cantabria	1383	***-10.10***	***-0.12***	-2.15	-3.52	-0.04	-0.72	-4.51	-0.05	-1.03
Castile-Leon	1360	0.99	0.01	0.15	***18.11***	***0.21***	3.25	0.65	0.00	0.11
Catalonia	1101	***16.49***	***0.19***	2.88	***16.12***	***0.19***	2.54	***18.42***	***0.21***	3.25
Galicia	1380	4.89	0.06	0.87	***23.26***	***0.28***	4.01	***13.42***	***0.16***	2.29
Navarre	1483	***21.28***	***0.25***	3.99	***22.83***	***0.27***	4.74	***22.70***	***0.26***	3.81
Rioja	1239	-5.39	-0.07	-1.06	8.25	0.10	1.77	-2.44	-0.03	-0.46

Source: Own compilation from PISA 2006 database.

The most significant impact of attending *GDPS* is observed in Navarre, where students present the highest significant and positive *ATT* in all disciplines, being the mean differential about 22 points in *PISA* score and 0.26 standard deviations from average total Spain *PISA* scores. A similar effect is observed in students from Basque Country or Catalonia, where all parameters are positive and significant. On the other hand, the significant superiority of *PS* students from Cantabria on mathematics should be highlighted; where non-treated students outperform 0.12 standard deviations treated ones. Secondly, we observe that the average impact of attending *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.

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 the essential variables in the educational production function once school choice has been done, such as the students' socioeconomic background, the peer-group effect or the school variables. So, in order to measure correctly the efficiency impact of attending *GDPS*, we estimate five output distance functions, one for each trio of plausible values, for both school types in each region[53].

First order output parameters are mostly positive and significant which means that the efficiency increases when, *ceteris paribus*, the performance in these subjects improves. 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 students efficiency keeping the output vector fixed. With the aim of check the best estimation each case, we use the likelihood test, which allow us to test the *translog* functional form, with(out) output-input separability, or the *quadratic* one.

Furthermore, in order to facilitate the interpretation of parameters, the original variables were transformed into deviation to the mean values, so first order input parameters should be interpreted as the partial elasticity[54] at mean values. We observe that the impact of socioeconomic background on achievements is generally higher for *GDPS* across regions; however students attending *PS* benefit more from the peer effect than their *GDPS* counterfactuals. The proportion of girls presents a positive impact on the student's performance,

[53] One hundred distance functions were estimated, although for the sake of simplicity we only report the average value for each school type and region in the Appendix of this paper.
[54] Note that the sign of the first order inputs parameters may be turned in order to facilitate the interpretation of output-input elasticities.

especially in *PS*, while the repeater or the immigrant conditions penalize the students' achievements, being this effect even higher in *PS*. Finally, boy students seem to perform better than girl ones.

From both, *GDPS* and *PS*, regional distance function estimations we may obtain the measurement of *ATTpf*. This one allows us to analyze the average impact of attending a *GDPS* after considering all educational inputs and placing each student on its own production frontier.

As we mentioned above, we may project each student to his/her production frontier and average the results or, instead this, selecting a group or a typical student to analyze the impact of attending a *GDPS*. For the sake of simplicity in this study the *ATTpf* and *ATTasi* are calculated for two hypothetical male non-repeater Spanish students (all dummy variables take value zero) with average inputs and control variables. We think that this mean student projected against the two production frontiers illustrate better the mean impact of attending a *GDPS* instead of averaging the results of all students with very different characteristics in terms of inputs and control variables.

Table 10 reports *ATTpf* in *PISA* score and in standard deviations from average total Spain *PISA* scores for each discipline[55].

Table 10: ATTpf in PISA score and in standard deviation across Regions

	Obs	*Mathematics*			*Reading*			*Science*		
Region	*N*	*ATTpf*	*ATTpf (Std.Dev)*	*t-value*	*ATTpf*	*ATTpf (Std.Dev)*	*t-value*	*ATTpf*	*ATTpf (Std.Dev)*	*t-value*
Andalusia	1,393	***13.13***	***0.15***	5.89	***12.59***	***0.15***	6.88	***13.44***	***0.16***	6.17
Aragon	1,376	***8.24***	***0.09***	2.71	***25.95***	***0.30***	2.57	***8.18***	***0.09***	2.85
Asturias	1,316	***10.07***	***0.12***	3.06	***9.66***	***0.11***	2.98	***10.28***	***0.12***	3.31
Basque Country	3,797	1.82	0.02	-0.11	1.71	0.02	-0.13	1.80	0.02	-0.12
Cantabria	1,383	***41.43***	***0.48***	29.20	***40.24***	***0.47***	29.91	***40.90***	***0.47***	31.58
Castile-Leon	1,360	-2.19	-0.03	-1.49	-2.06	-0.02	-1.62	-2.22	-0.03	-1.54
Catalonia	1,101	***38.65***	***0.44***	14.86	***35.96***	***0.42***	14.14	***39.13***	***0.45***	13.43
Galicia	1,380	***24.09***	***0.28***	4.43	***23.57***	***0.28***	4.15	***24.36***	***0.28***	4.35
Navarre	1,483	***25.80***	***0.30***	7.48	***25.22***	***0.30***	7.95	***26.30***	***0.30***	7.61
Rioja	1,239	***62.36***	***0.72***	22.75	***57.79***	***0.68***	21.33	***61.54***	***0.71***	22.36

Source: Own compilation from PISA 2006 database.

Figures from Table 10 show a predominance of the *GDPS* on academic achievement in all disciplines after all educational determinants are considered. Hence, once the educational inputs and the full efficiency are taking into account, *GDPS* students, close to the mean values

[55] Three predicted values (Mathematics, Reading and Science), one for each distance function estimation, are obtained.

in inputs and control variables, perform significantly better than their public counterparts in all regions and subjects, with the exception of Basque Country where no significant differences are found and Castile-Leon, where this gap favors public school students. *GDPS* advantage is about 0.72 (0.48) standard deviations from average total Spain *PISA* scores in Rioja (Cantabria). We also observe a higher variability of the school type impact across regions, which differs from 0.75 standard deviations from average *PISA* scores between students from Castile-Leon and Rioja to 0.24 between students from Castile-Leon and Cantabria, being these differences 0.33 and 0.06 using *ATT* measure. On the other hand, the students' results differences by school ownership measure using *ATTpf* are generally lower (higher) on Reading (Mathematics and Science).

4.3. Average Treatment Effect on the Treated assuming school inefficiency

The last step of our procedure is to correct the *ATTpf* measurement across regions in order to allow for school types divergences in the students' performance once the efficiency component is taken into account. From our point of view, this measurement is a good tool to test whether exists or not equality of educational opportunities within each region. Table 11 reports *ATTasi* 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 regarding to *ATTpf*. Secondly, some regions present a higher average[56] impact of attending a *GDPS* using *ATTasi* compared to *ATTpf*, such as Basque Country, Cantabria, Castile-Leon, Galicia and La Rioja. Hence, *GDPS* students are relatively more efficient that *PS* ones in these last regions. On the contrary, in Andalusia, Aragon Asturias, Catalonia, and Navarre, the average *ATTpf* values are higher than *ATTasi* are. These last results indicate the performance of public school students in those regions improve using *ATTasi*, which suggests there are some divergences in efficiency between both school types across regions. In addition to this, Cantabria, Galicia and La Rioja are the regions with the higher *ATTasi* values. We think that in these three regions the educational equality of opportunities could be in danger if the school choice actually matters in terms of higher test scores of *GDPS*. Nevertheless, more research is still necessary in order to analyze the evolution of this result.

On the other hand, Castile-Leon is the only region where there are no relevant differences between both educational systems. It is worth to highlight here that, whereas the average impact of attending a *GDPS* is negative on the production frontier (*ATTpf*= -2.19 on Math), this value turns to zero considering mean student efficiency divergences in both school

[56] This measure refers to the average of the *ATTpf* in the three disciplines for each school type and region.

types (*ATTasi*= 0). In other words, in this region the best option for a family who is seeking a school would be to attend the most efficient *PS*. However without any efficiency information the second best would be a more efficient (at the mean value) *GDPS*.

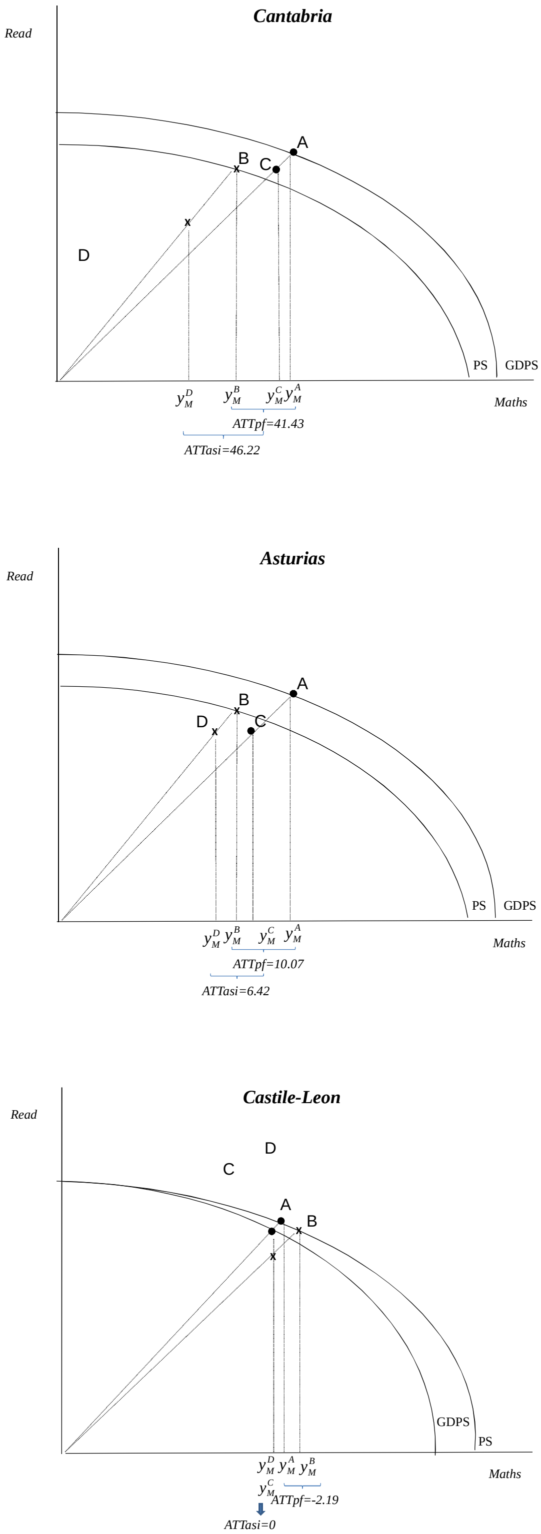
Table 11: ATTasi in PISA score and in standard deviation across Regions

	Obs	*Mathematics*			*Reading*			*Science*		
Region	*N*	*ATTasi*	*ATTasi (Std.Dev)*	*t-value*	*ATTasi*	*ATTasi (Std.Dev)*	*t-value*	*ATTasi*	*ATTasi (Std.Dev)*	*t-value*
Andalusia	1,393	***12.83***	***0.15***	12.76	***12.30***	***0.14***	12.96	***13.14***	***0.15***	12.72
Aragon	1,376	***10.92***	***0.13***	7.98	***10.28***	***0.12***	8.31	***10.97***	***0.13***	11.13
Asturias	1,316	***6.42***	***0.07***	1.78	***6.15***	***0.07***	1.77	***6.55***	***0.08***	1.81
Basque Country	3,797	2.69	0.03	1.02	2.52	0.03	1.19	2.66	0.03	1.20
Cantabria	1,383	***46.22***	***0.53***	81.23	***44.89***	***0.53***	75.90	***45.63***	***0.53***	112.74
Catille-Leon	1,360	0.08	0.00	-0.27	0.08	0.00	-0.29	0.08	0.00	-0.28
Catalonia	1,101	***27.24***	***0.31***	16.58	***25.35***	***0.30***	16.25	***27.58***	***0.32***	14.95
Galicia	1,380	***31.76***	***0.36***	14.19	***31.09***	***0.36***	13.25	***32.12***	***0.37***	15.09
Navarre	1,483	***15.61***	***0.18***	7.37	***15.29***	***0.18***	6.70	***15.89***	***0.18***	7.12
Rioja	1,239	***64.17***	***0.74***	58.04	***59.46***	***0.70***	50.80	***63.32***	***0.73***	65.66

Source: Own compilation from PISA 2006 database.

In order to illustrate the potentiality of our approach, Figure 2 shows three different examples of *ATTpf* and *ATTasi* in Mathematics for Asturias, Cantabria and Castile-Leon respectively. As we can see, *GDPS* frontier (*GDPS*) is always above the public one (*PS*), which implies a better technology transforming educational inputs into academic attainments. The first graph (Cantabria) represents the situation where the impact of attending a *GDPS* is higher when *ATTasi* is used instead of *ATTpf*. This information points out that, once taken into account the mean efficiency in both school types, *GDPS* students perform even better than *PS* ones. This result suggests a significant management problem in *PS* compared with *GDPS*. In Asturias the situation is similar, however *ATTpf* is higher than *ATTasi* and this means that when mean efficiency is considered the gap between both school types reduces from 10.07 to 6.42, pointing out that *PS* are more efficient than *GDPS*. Finally, Castile-Leon represents the only case where the difference in favor of *PS* using *ATTpf* reverses to zero considering *ATTasi*. This situation seems to indicate that although best schools are *public managed* this group is more inefficient on average than their government-dependent private counterparts.

Figure 2: Some ATTpf and ATTasi examples for Cantabria, Asturias and Castile-Leon



Source: Own compilation

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 between different 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 the educational differences by school type from the *PSM* sub-samples. 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 assuming school inefficiency (*ATTasi*).

Following this aim two different output distance functions were estimated by school ownership, using *PSM* subsample in each Spanish region for both, *PS* and *GDPS*. The results in terms of *ATTasi* seem to reflect divergences in performance between both school types and across regions. Hence, we observe that *GDPS* students perform significantly better than *PS* ones in Andalusia, 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 generally 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 Spanish region where *PS* students perform better than *GDPS*.

We think that our model allows us to detect the best schools in terms of efficiency in order to use these references to do benchmarking for government dependent private schools and public ones. Moreover, we consider that this approach is a good tool to measure and to supervise the equality of educational opportunities concept. From our point of view it is not admissible that a student could be penalized in more than half standard deviation due to technological and efficiency differences between publicly financed schools.

To summarize we do believe that the conceptual framework presented in this paper, based on the joint use of *PSM* and distance function at the student level, together with the two new measurements for reflecting the school type differences. Furthermore, this approach provides an appealing methodology for policy makers in order to benchmark the best educational practices, avoiding unfair comparisons between the *government dependent private* and the public systems. However, a similar analysis should be developed continuously in time to evaluate the evolution of these results to ensure the equality of the educational opportunities in Spain and with the clear purpose of improving the educational efficiency.

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APPENDIX[57]

Table1: Stochastic Distance Function for GDPS in Andalusia

Variables	*Coeff.*	*Std. Dev*	*p-value*	*Variables*	*Coeff.*	*Std. Dev.*	*p-value*
Intercept	**-0.306**	0.099	0.006	$(Lnx_1)^2$	0.085	0.363	0.722
Outputs				$(Lnx_2)^2$	0.418	0.353	0.253
Lny_1 (*math score*)	0.392			$(Lnx_3)^2$	1.912	4.552	0.511
Lny_2 (*reading score*)	**0.510**	0.134	0.000	$(Lnx_4)^2$	-0.269	8.093	0.614
Lny_3 (*science score*)	0.098	0.184	0.554	$(Lnx_1)(Lnx_2)$	0.135	0.172	0.538
$(Lny_1)^2$	3.924			$(Lnx_1)(Lnx_3)$	0.009	1.614	0.627
$(Lny_2)^2$	**2.419**	0.632	0.000	$(Lnx_1)(Lnx_4)$	1.120	1.318	0.437
$(Lny_3)^2$	**4.443**	1.426	0.015	$(Lnx_2)(Lnx_3)$	-0.268	0.430	0.609
$(Lny_1)(Lny_2)$	-0.950			$(Lnx_2)(Lnx_4)$	0.283	0.382	0.504
$(Lny_1)(Lny_3)$	-2.974			$(Lnx_3)(Lnx_4)$	0.280	2.220	0.535
$(Lny_2)(Lny_3)$	-1.469	0.799	0.147	***Input-output***			
Inputs				$(Lnx_1)(Lny_1)$	-0.693		
Lnx_1 (*Scmatedu*)	-0.080	0.214	0.696	$(Lnx_1)(Lny_2)$	0.413	0.317	0.241
Lnx_2 (*Ecsc*)	-0.099	0.071	0.253	$(Lnx_1)(Lny_3)$	-0.305	0.435	0.635
Lnx_3 (*Peer*)	-0.211	0.757	0.458	$(Lnx_2)(Lny_1)$	-0.216		
Lnx_4 (*Pcgirls*)	0.011	0.609	0.409	$(Lnx_2)(Lny_2)$	0.521	0.344	0.206
x_5 (*Repone*)	**0.131**	0.016	0.000	$(Lnx_2)(Lny_3)$	1.075	0.510	0.440
x_6 (*Repmore*)	**0.229**	0.021	0.000	$(Lnx_3)(Lny_1)$	-0.474		
Lnx_7 (*Stratio*)	-0.091	0.216	0.569	$(Lnx_3)(Lny_2)$	-0.601	0.718	0.353
Lnx_8 (*Schsize*)	0.013	0.040	0.640	$(Lnx_3)(Lny_3)$	-1.411	1.086	0.493
x_9 (*Firstgen*)	*omitted*	*omitted*	*omitted*	$(Lnx_4)(Lny_1)$	0.292		
x_{10} (*Secgen*)	-0.171	0.109	0.139	$(Lnx_4)(Lny_2)$	1.118	0.682	0.160
x_{11} (*Gender*)	0.021	0.014	0.150	$(Lnx_4)(Lny_3)$	-0.082	0.953	0.586
Sigma-v	**-5.504**	0.285	0.000	*Mean Eff.*	0.725	0.070	
Sigma-u	**-3.678**	0.183	0.000	*N*	353		

Source: Own compilation from PISA 2006 database

[57] We point out in bold type the significant figures at 99%.

Table 2: Stochastic Distance Function for PS in Andalusia

Variables	*Coeff.*	*Std. Dev*	*p-value*	*Variables*	*Coeff.*	*Std. Dev.*	*p-value*
Intercept	**-0.267**	0.013	0.000	$(Lnx_1)^2$	-0.132	0.072	0.146
Outputs				$(Lnx_2)^2$	0.260	0.222	0.258
Lny_1 (*math score*)	0.582			$(Lnx_3)^2$	1.017	1.381	0.465
Lny_2 (*reading score*)	**0.231**	0.049	0.000	$(Lnx_4)^2$	**2.022**	0.695	0.009
Lny_3 (*science score*)	**0.187**	0.061	0.008	$(Lnx_1)(Lnx_2)$	0.104	0.076	0.190
$(Lny_1)^2$	3.644			$(Lnx_1)(Lnx_3)$	0.508	0.362	0.234
$(Lny_2)^2$	**1.548**	0.214	0.000	$(Lnx_1)(Lnx_4)$	**0.728**	0.258	0.006
$(Lny_3)^2$	**5.029**	0.570	0.000	$(Lnx_2)(Lnx_3)$	-0.101	0.381	0.757
$(Lny_1)(Lny_2)$	-0.082			$(Lnx_2)(Lnx_4)$	0.286	0.264	0.352
$(Lny_1)(Lny_3)$	-3.562			$(Lnx_3)(Lnx_4)$	1.135	0.989	0.393
$(Lny_2)(Lny_3)$	**-1.467**	0.295	0.000	***Input-output***			
Inputs				$(Lnx_1)(Lny_1)$	-0.021		
Lnx_1 (*Scmatedu*)	**0.045**	0.019	0.039	$(Lnx_1)(Lny_2)$	-0.107	0.117	0.391
Lnx_2 (*Ecsc*)	**-0.140**	0.028	0.000	$(Lnx_1)(Lny_3)$	0.129	0.160	0.375
Lnx_3 (*Peer*)	**-0.231**	0.082	0.011	$(Lnx_2)(Lny_1)$	0.105		
Lnx_4 (*Pcgirls*)	-0.068	0.072	0.209	$(Lnx_2)(Lny_2)$	-0.131	0.223	0.539
x_5 (*Repone*)	**0.149**	0.009	0.000	$(Lnx_2)(Lny_3)$	0.026	0.301	0.633
x_6 (*Repmore*)	**0.285**	0.015	0.000	$(Lnx_3)(Lny_1)$	0.505		
Lnx_7 (*Stratio*)	0.024	0.044	0.669	$(Lnx_3)(Lny_2)$	-0.098	0.595	0.753
Lnx_8 (*Schsize*)	-0.008	0.013	0.496	$(Lnx_3)(Lny_3)$	-0.406	0.775	0.575
x_9 (*Firstgen*)	-0.023	0.084	0.688	$(Lnx_4)(Lny_1)$	-0.849		
x_{10} (*Secgen*)	0.064	0.069	0.433	$(Lnx_4)(Lny_2)$	0.182	0.445	0.241
x_{11} (*Gender*)	**0.034**	0.008	0.000	$(Lnx_4)(Lny_3)$	0.667	0.569	0.405
Sigma-v	**-5.075**	0.148	0.000	*Mean Eff.*	0.881	0.065	
Sigma-u	**-3.653**	0.127	0.000	*N*	1,039		

Source: Own compilation from PISA 2006 database

Table 3: Stochastic Distance Function for GDPS in Aragon

Variables	***Coeff.***	***Std. Dev***	***p-value***	***Variables***	***Coeff.***	***Std. Dev.***	***p-value***
Intercept	**-0.180**	0.025	0.000	x_6 (*Repmore*)	**0.269**	0.026	0.000
Outputs				Lnx_7 (*Stratio*)	**0.104**	0.054	0.055
Lny_1 (*math score*)	*0.117*			Lnx_8 (*Schsize*)	-0.005	0.017	0.768
Lny_2 (*reading score*)	**0.366**	0.043	0.000	x_9 (*Firstgen*)	-0.021	0.041	0.342
Lny_3 (*science score*)	**0.518**	0.067	0.000	x_{10} (*Secgen*)	-0.006	0.074	0.627
$(Lny_1)^2$	*1.628*			x_{11} (*Gender*)	0.004	0.011	0.487
$(Lny_2)^2$	**0.976**	0.180	0.000	$(Lnx_1)^2$	0.060	0.100	0.557
$(Lny_3)^2$	**2.453**	0.643	0.002	$(Lnx_2)^2$	0.266	0.319	0.169
$(Lny_1)(Lny_2)$	*-0.076*			$(Lnx_3)^2$	**-6.862**	2.956	0.064
$(Lny_1)(Lny_3)$	*-1.553*			$(Lnx_4)^2$	0.516	0.333	0.132
$(Lny_2)(Lny_3)$	**-0.900**	0.256	0.011	$(Lnx_1)(Lnx_2)$	0.015	0.090	0.625
Inputs				$(Lnx_1)(Lnx_3)$	-0.760	0.629	0.319
Lnx_1 (*Scmatedu*)	-0.009	0.030	0.651	$(Lnx_1)(Lnx_4)$	0.005	0.131	0.649
Lnx_2 (*Ecsc*)	**-0.168**	0.038	0.000	$(Lnx_2)(Lnx_3)$	0.572	0.612	0.438
Lnx_3 (*Peer*)	0.428	0.185	0.168	$(Lnx_2)(Lnx_4)$	0.115	0.185	0.487
Lnx_4 (*Pcgirls*)	0.009	0.075	0.852	$(Lnx_3)(Lnx_4)$	-0.834	0.789	0.314
x_5 (*Repone*)	**0.134**	0.013	0.000				
Sigma-v	**-5.283**	0.224	0.000	*Mean Eff.*	0.887	0.063	
Sigma-u	**-3.751**	0.181	0.000	*N*	451		

Source: Own compilation from PISA 2006 database

Table 4: Stochastic Distance Function for PS in Aragon

Variables	*Coeff.*	*Std. Dev*	*p-value*	*Variables*	*Coeff.*	*Std. Dev.*	*p-value*
Intercept	**-0.244**	0.015	0.000	x_6 (*Repmore*)	**0.267**	0.017	0.000
Outputs				Lnx_7 (*Stratio*)	**0.104**	0.048	0.036
Lny_1 (*math score*)	0.226			Lnx_8 (*Schsize*)	0.007	0.014	0.611
Lny_2 (*reading score*)	**0.391**	0.033	0.000	x_9 (*Firstgen*)	**0.058**	0.016	0.000
Lny_3 (*science score*)	**0.383**	0.047	0.000	x_{10} (*Secgen*)	0.057	0.054	0.329
$(Lny_1)^2$	*2.901*			x_{11} (*Gender*)	-0.011	0.009	0.261
$(Lny_2)^2$	**1.088**	0.103	0.000	$(Lnx_1)^2$	0.072	0.074	0.346
$(Lny_3)^2$	**2.330**	0.532	0.000	$(Lnx_2)^2$	**-0.459**	0.245	0.071
$(Lny_1)(Lny_2)$	*-0.830*			$(Lnx_3)^2$	2.899	1.927	0.150
$(Lny_1)(Lny_3)$	*-2.071*			$(Lnx_4)^2$	0.553	0.430	0.225
$(Lny_2)(Lny_3)$	-0.258	0.226	0.333	$(Lnx_1)(Lnx_2)$	0.057	0.078	0.475
Inputs				$(Lnx_1)(Lnx_3)$	-0.045	0.421	0.872
Lnx_1 (*Scmatedu*)	-0.022	0.021	0.322	$(Lnx_1)(Lnx_4)$	-0.156	0.173	0.384
Lnx_2 (*Ecsc*)	**-0.091**	0.028	0.002	$(Lnx_2)(Lnx_3)$	**1.351**	0.447	0.003
Lnx_3 (*Peer*)	-0.057	0.096	0.587	$(Lnx_2)(Lnx_4)$	-0.094	0.181	0.615
Lnx_4 (*Pcgirls*)	0.007	0.061	0.763	$(Lnx_3)(Lnx_4)$	-0.361	0.711	0.625
x_5 (*Repone*)	**0.130**	0.010	0.000				
Sigma-v	**-5.049**	0.143	0.000	*Mean Eff.*	0.881	0.065	
Sigma-u	**-3.650**	0.125	0.000	*N*	924		

Source: Own compilation from PISA 2006 database

Table 5: Stochastic Distance Function for GDPS in Asturias

Variables	***Coeff.***	***Std. Dev***	***p-value***	***Variables***	***Coeff.***	***Std. Dev.***	***p-value***
Intercept	**-0.207**	0.040	0.000	$(Lnx_1)^2$	0.049	0.229	0.637
Outputs				$(Lnx_2)^2$	-0.372	0.390	0.406
Lny_1 (*math score*)	*0.451*			$(Lnx_3)^2$	**-14.466**	5.698	0.016
Lny_2 (*reading score*)	**0.254**	0.084	0.014	$(Lnx_4)^2$	**5.487**	2.995	0.081
Lny_3 (*science score*)	**0.295**	0.123	0.039	$(Lnx_1)(Lnx_2)$	**-0.244**	0.108	0.048
$(Lny_1)^2$	*3.425*			$(Lnx_1)(Lnx_3)$	**1.239**	0.441	0.014
$(Lny_2)^2$	**2.300**	0.497	0.000	$(Lnx_1)(Lnx_4)$	**0.692**	0.273	0.013
$(Lny_3)^2$	**3.199**	1.003	0.007	$(Lnx_2)(Lnx_3)$	**1.632**	0.714	0.045
$(Lny_1)(Lny_2)$	*-1.263*			$(Lnx_2)(Lnx_4)$	-0.466	0.443	0.367
$(Lny_1)(Lny_3)$	*-2.162*			$(Lnx_3)(Lnx_4)$	-1.390	1.737	0.459
$(Lny_2)(Lny_3)$	-1.037	0.648	0.216	***Input-output***			
Inputs				$(Lnx_1)(Lny_1)$	*-0.139*		
Lnx_1 (*Scmatedu*)	-0.018	0.101	0.640	$(Lnx_1)(Lny_2)$	-0.120	0.149	0.441
Lnx_2 (*Ecsc*)	**-0.233**	0.057	0.000	$(Lnx_1)(Lny_3)$	0.259	0.222	0.301
Lnx_3 (*Peer*)	-0.232	0.444	0.620	$(Lnx_2)(Lny_1)$	*0.106*		
Lnx_4 (*Pcgirls*)	0.289	0.168	0.114	$(Lnx_2)(Lny_2)$	0.341	0.337	0.351
x_5 (*Repone*)	**0.147**	0.013	0.000	$(Lnx_2)(Lny_3)$	-0.447	0.509	0.450
x_6 (*Repmore*)	**0.244**	0.027	0.000	$(Lnx_3)(Lny_1)$	*0.224*		
Lnx_7 (*Stratio*)	-0.032	0.080	0.676	$(Lnx_3)(Lny_2)$	-0.310	0.818	0.629
Lnx_8 (*Schsize*)	0.048	0.037	0.214	$(Lnx_3)(Lny_3)$	0.086	1.270	0.554
x_9 (*Firstgen*)	0.011	0.049	0.657	$(Lnx_4)(Lny_1)$	*-0.283*		
x_{10} (*Secgen*)	**0.316**	0.103	0.006	$(Lnx_4)(Lny_2)$	**-1.152**	0.504	0.040
x_{11} (*Gender*)	**0.025**	0.012	0.066	$(Lnx_4)(Lny_3)$	**1.435**	0.748	0.089
Sigma-v	**-5.438**	0.238	0.000	*Mean Eff.*	0.900	0.056	
Sigma-u	**-4.019**	0.205	0.000	*N*	374		

Source: Own compilation from PISA 2006 database

Table 6: Stochastic Distance Function for PS in Asturias

Variables	*Coeff.*	*Std. Dev*	*p-value*	*Variables*	*Coeff.*	*Std. Dev.*	*p-value*
Intercept	**-0.231**	0.016	0.000	$(\text{Lnx}_1)^2$	**0.201**	0.062	0.001
Outputs				$(\text{Lnx}_2)^2$	-0.192	0.206	0.369
Lny_1 (*math score*)	*0.434*			$(\text{Lnx}_3)^2$	3.329	2.699	0.229
Lny_2 (*reading score*)	**0.310**	0.042	0.000	$(\text{Lnx}_4)^2$	**1.303**	0.358	0.001
Lny_3 (*science score*)	**0.256**	0.054	0.000	$(\text{Lnx}_1)(\text{Lnx}_2)$	-0.109	0.064	0.102
$(\text{Lny}_1)^2$	*2.653*			$(\text{Lnx}_1)(\text{Lnx}_3)$	**1.145**	0.266	0.000
$(\text{Lny}_2)^2$	**2.363**	0.284	0.000	$(\text{Lnx}_1)(\text{Lnx}_4)$	**0.770**	0.134	0.000
$(\text{Lny}_3)^2$	**4.059**	0.627	0.000	$(\text{Lnx}_2)(\text{Lnx}_3)$	-0.436	0.446	0.360
$(\text{Lny}_1)(\text{Lny}_2)$	*-0.479*			$(\text{Lnx}_2)(\text{Lnx}_4)$	0.035	0.169	0.835
$(\text{Lny}_1)(\text{Lny}_3)$	*-2.174*			$(\text{Lnx}_3)(\text{Lnx}_4)$	-0.791	0.825	0.359
$(\text{Lny}_2)(\text{Lny}_3)$	**-1.884**	0.326	0.000	***Input-output***			
Inputs				$(\text{Lnx}_1)(\text{Lny}_1)$	*0.075*		
Lnx_1 (*Scmatedu*)	**-0.076**	0.018	0.000	$(\text{Lnx}_1)(\text{Lny}_2)$	0.039	0.104	0.600
Lnx_2 (*Ecsc*)	**-0.116**	0.026	0.000	$(\text{Lnx}_1)(\text{Lny}_3)$	-0.113	0.147	0.422
Lnx_3 (*Peer*)	-0.205	0.121	0.115	$(\text{Lnx}_2)(\text{Lny}_1)$	*-0.116*		
Lnx_4 (*Pcgirls*)	-0.059	0.048	0.229	$(\text{Lnx}_2)(\text{Lny}_2)$	-0.009	0.188	0.599
x_5 (*Repone*)	**0.124**	0.009	0.000	$(\text{Lnx}_2)(\text{Lny}_3)$	0.125	0.276	0.466
x_6 (*Repmore*)	**0.255**	0.018	0.000	$(\text{Lnx}_3)(\text{Lny}_1)$	*-1.025*		
Lnx_7 (*Stratio*)	**0.124**	0.052	0.026	$(\text{Lnx}_3)(\text{Lny}_2)$	0.489	0.627	0.509
Lnx_8 (*Schsize*)	-0.017	0.016	0.326	$(\text{Lnx}_3)(\text{Lny}_3)$	0.535	0.875	0.574
x_9 (*Firstgen*)	-0.028	0.026	0.340	$(\text{Lnx}_4)(\text{Lny}_1)$	*0.577*		
x_{10} (*Secgen*)	0.024	0.055	0.600	$(\text{Lnx}_4)(\text{Lny}_2)$	-0.495	0.248	0.114
x_{11} (*Gender*)	**0.020**	0.008	0.019	$(\text{Lnx}_4)(\text{Lny}_3)$	-0.081	0.331	0.557
Sigma-v	**-5.136**	0.154	0.000	*Mean Eff.*	0.898	0.053	
Sigma-u	**-4.001**	0.167	0.000	*N*	941		

Source: Own compilation from PISA 2006 database

Table 7: Stochastic Distance Function for GDPS in Basque Country

Variables	***Coeff.***	***Std. Dev***	***p-value***	***Variables***	***Coeff.***	***Std. Dev.***	***p-value***
Intercept	**-0.163**	-0.010	0.000	$(Lnx_1)^2$	**-0.094**	0.038	0.014
Outputs				$(Lnx_2)^2$	0.002	0.186	0.782
Lny_1 (*math score*)	*0.513*			$(Lnx_3)^2$	-1.529	0.955	0.143
Lny_2 (*reading score*)	**0.300**	0.026	0.000	$(Lnx_4)^2$	-0.632	0.659	0.421
Lny_3 (*science score*)	**0.187**	0.033	0.000	$(Lnx_1)(Lnx_2)$	-0.086	0.057	0.147
$(Lny_1)^2$	*3.637*			$(Lnx_1)(Lnx_3)$	-0.076	0.130	0.571
$(Lny_2)^2$	**2.552**	0.213	0.000	$(Lnx_1)(Lnx_4)$	-0.194	0.207	0.365
$(Lny_3)^2$	**5.620**	0.504	0.000	$(Lnx_2)(Lnx_3)$	-0.346	0.283	0.235
$(Lny_1)(Lny_2)$	*-0.284*			$(Lnx_2)(Lnx_4)$	-0.220	0.282	0.435
$(Lny_1)(Lny_3)$	*-3.353*			$(Lnx_3)(Lnx_4)$	0.861	0.664	0.222
$(Lny_2)(Lny_3)$	**-2.267**	0.279	0.000	***Input-output***			
Inputs				$(Lnx_1)(Lny_1)$	*-0.111*		
Lnx_1 (*Scmatedu*)	-0.012	0.011	0.294	$(Lnx_1)(Lny_2)$	-0.053	0.071	0.510
Lnx_2 (*Ecsc*)	**-0.094**	0.019	0.000	$(Lnx_1)(Lny_3)$	0.164	0.098	0.182
Lnx_3 (*Peer*)	**-0.145**	0.044	0.001	$(Lnx_2)(Lny_1)$	*-0.100*		
Lnx_4 (*Pcgirls*)	**-0.157**	0.058	0.020	$(Lnx_2)(Lny_2)$	-0.031	0.155	0.693
x_5 (*Repone*)	**0.147**	0.007	0.000	$(Lnx_2)(Lny_3)$	0.130	0.218	0.618
x_6 (*Repmore*)	**0.260**	0.019	0.000	$(Lnx_3)(Lny_1)$	*0.103*		
Lnx_7 (*Stratio*)	0.026	0.016	0.128	$(Lnx_3)(Lny_2)$	**0.714**	0.363	0.062
Lnx_8 (*Schsize*)	**-0.020**	0.005	0.000	$(Lnx_3)(Lny_3)$	-0.817	0.473	0.115
x_9 (*Firstgen*)	0.027	0.021	0.209	$(Lnx_4)(Lny_1)$	*0.138*		
x_{10} (*Secgen*)	-0.017	0.081	0.734	$(Lnx_4)(Lny_2)$	-0.011	0.403	0.602
x_{11} (*Gender*)	0.009	0.005	0.109	$(Lnx_4)(Lny_3)$	-0.128	0.533	0.426
Sigma-v	**-5.029**	-0.099	0.000	*Mean Eff.*	0.895	0.054	
Sigma-u	**-3.948**	-0.109	0.000	*N*	2,255		

Source: Own compilation from PISA 2006 database

Table 8: Stochastic Distance Function for PS in Basque Country

Variables	***Coeff.***	***Std. Dev***	***p-value***	***Variables***	***Coeff.***	***Std. Dev.***	***p-value***
Intercept	**-0.210**	0.014	0.000	$(Lnx_1)^2$	**0.089**	0.036	0.017
Outputs				$(Lnx_2)^2$	0.310	0.216	0.214
Lny_1 (*math score*)	*0.524*			$(Lnx_3)^2$	0.159	0.997	0.724
Lny_2 (*reading score*)	**0.249**	0.036	0.000	$(Lnx_4)^2$	**4.730**	2.320	0.060
Lny_3 (*science score*)	**0.227**	0.046	0.000	$(Lnx_1)(Lnx_2)$	-0.068	0.049	0.177
$(Lny_1)^2$	*2.921*			$(Lnx_1)(Lnx_3)$	**0.387**	0.151	0.012
$(Lny_2)^2$	**0.970**	0.137	0.000	$(Lnx_1)(Lnx_4)$	-0.320	0.198	0.146
$(Lny_3)^2$	**3.297**	0.465	0.000	$(Lnx_2)(Lnx_3)$	-0.406	0.344	0.284
$(Lny_1)(Lny_2)$	*-0.297*			$(Lnx_2)(Lnx_4)$	0.507	0.403	0.229
$(Lny_1)(Lny_3)$	*-2.624*			$(Lnx_3)(Lnx_4)$	**-2.581**	1.327	0.075
$(Lny_2)(Lny_3)$	-0.673	0.238	0.126	***Input-output***			
Inputs				$(Lnx_1)(Lny_1)$	*-0.035*		
Lnx_1 (*Scmatedu*)	0.009	0.012	0.460	$(Lnx_1)(Lny_2)$	**0.200**	0.063	0.012
Lnx_2 (*Ecsc*)	**-0.086**	0.025	0.001	$(Lnx_1)(Lny_3)$	-0.165	0.089	0.165
Lnx_3 (*Peer*)	**-0.285**	0.070	0.000	$(Lnx_2)(Lny_1)$	*-0.184*		
Lnx_4 (*Pcgirls*)	-0.143	0.098	0.157	$(Lnx_2)(Lny_2)$	-0.114	0.160	0.497
x_5 (*Repone*)	**0.163**	0.008	0.000	$(Lnx_2)(Lny_3)$	0.298	0.215	0.255
x_6 (*Repmore*)	**0.297**	0.014	0.000	$(Lnx_3)(Lny_1)$	*-0.066*		
Lnx_7 (*Stratio*)	0.020	0.023	0.388	$(Lnx_3)(Lny_2)$	0.402	0.429	0.366
Lnx_8 (*Schsize*)	0.010	0.007	0.213	$(Lnx_3)(Lny_3)$	-0.336	0.543	0.589
x_9 (*Firstgen*)	**0.052**	0.014	0.000	$(Lnx_4)(Lny_1)$	*-0.073*		
x_{10} (*Secgen*)	-0.054	0.042	0.262	$(Lnx_4)(Lny_2)$	1.086	0.563	0.130
x_{11} (*Gender*)	0.008	0.007	0.208	$(Lnx_4)(Lny_3)$	-1.014	0.719	0.193
Sigma-v	**-5.142**	0.120	0.000	*Mean Eff.*	0.879	0.067	
Sigma-u	**-3.622**	0.097	0.000	*N*	1,541		

Source: Own compilation from PISA 2006 database

Table 9: Stochastic Distance Function for GDPS in Cantabria

Variables	*Coeff.*	*Std. Dev*	*p-value*	*Variables*	*Coeff.*	*Std. Dev.*	*p-value*
Intercept	**-0.216**	0.031	0.000	x_6 (*Repmore*)	**0.232**	0.025	0.000
Outputs				Lnx_7 (*Stratio*)	0.020	0.054	0.720
Lny_1 (*math score*)	*0.544*			Lnx_8 (*Schsize*)	0.001	0.015	0.760
Lny_2 (*reading score*)	**0.250**	0.048	0.000	x_9 (*Firstgen*)	0.061	0.026	0.028
Lny_3 (*science score*)	**0.206**	0.062	0.002	x_{10} (*Secgen*)	0.117	0.100	0.286
$(Lny_1)^2$	*4.728*			x_{11} (*Gender*)	**0.019**	0.010	0.082
$(Lny_2)^2$	**1.798**	0.401	0.000	$(Lnx_1)^2$	**0.203**	0.070	0.004
$(Lny_3)^2$	**3.816**	0.638	0.000	$(Lnx_2)^2$	-0.602	0.350	0.119
$(Lny_1)(Lny_2)$	*-1.355*			$(Lnx_3)^2$	0.535	1.787	0.773
$(Lny_1)(Lny_3)$	*-3.373*			$(Lnx_4)^2$	**2.142**	0.637	0.001
$(Lny_2)(Lny_3)$	-0.443	0.390	0.361	$(Lnx_1)(Lnx_2)$	**-0.265**	0.101	0.011
Inputs				$(Lnx_1)(Lnx_3)$	-0.096	0.392	0.786
Lnx_1 (*Scmatedu*)	0.054	0.031	0.101	$(Lnx_1)(Lnx_4)$	-0.063	0.230	0.734
Lnx_2 (*Ecsc*)	**-0.217**	0.036	0.000	$(Lnx_2)(Lnx_3)$	0.905	0.508	0.094
Lnx_3 (*Peer*)	-0.244	0.181	0.182	$(Lnx_2)(Lnx_4)$	-0.111	0.245	0.550
Lnx_4 (*Pcgirls*)	0.107	0.080	0.221	$(Lnx_3)(Lnx_4)$	**-2.026**	0.640	0.002
x_5 (*Repone*)	**0.152**	0.012	0.000				
Sigma-v	**-5.464**	0.242	0.000	*Mean Eff.*	0.896	0.059	
Sigma-u	**-3.946**	0.193	0.000	*N*	*489*		

Source: Own compilation from PISA 2006 database

Table 10: Stochastic Distance Function for PS in Cantabria

Variables	*Coeff.*	*Std. Dev*	*p-value*	*Variables*	*Coeff.*	*Std. Dev.*	*p-value*
Intercept	**-0.199**	0.017	0.000	x_6 (*Repmore*)	**0.283**	0.016	0.000
Outputs				Lnx_7 (*Stratio*)	-0.060	0.046	0.210
Lny_1 (*math score*)	0.445			Lnx_8 (*Schsize*)	-0.016	0.020	0.478
Lny_2 (*reading score*)	**0.262**	0.036	0.000	x_9 (*Firstgen*)	**0.057**	0.022	0.018
Lny_3 (*science score*)	**0.293**	0.048	0.000	x_{10} (*Secgen*)	0.073	0.106	0.522
$(Lny_1)^2$	2.568			x_{11} (*Gender*)	**0.021**	0.008	0.013
$(Lny_2)^2$	**0.673**	0.102	0.000	$(Lnx_1)^2$	**-0.116**	0.064	0.078
$(Lny_3)^2$	**2.880**	0.435	0.000	$(Lnx_2)^2$	-0.275	0.238	0.265
$(Lny_1)(Lny_2)$	*-0.181*			$(Lnx_3)^2$	2.927	2.646	0.293
$(Lny_1)(Lny_3)$	*-2.387*			$(Lnx_4)^2$	-0.194	0.172	0.271
$(Lny_2)(Lny_3)$	**-0.492**	0.175	0.040	$(Lnx_1)(Lnx_2)$	0.021	0.078	0.776
Inputs				$(Lnx_1)(Lnx_3)$	**-1.067**	0.495	0.040
Lnx_1 (*Scmatedu*)	-0.021	0.015	0.163	$(Lnx_1)(Lnx_4)$	0.438	0.250	0.123
Lnx_2 (*Ecsc*)	**-0.170**	0.028	0.000	$(Lnx_2)(Lnx_3)$	-0.323	0.560	0.571
Lnx_3 (*Peer*)	-0.426	0.103	0.000	$(Lnx_2)(Lnx_4)$	0.115	0.149	0.471
Lnx_4 (*Pcgirls*)	-0.017	0.052	0.658	$(Lnx_3)(Lnx_4)$	0.324	0.723	0.556
x_5 (*Repone*)	**0.149**	0.008	0.000				
Sigma-v	**-5.221**	0.171	0.000	*Mean Eff.*	0.892	0.059	
Sigma-u	**-3.866**	0.152	0.000	*N*	894		

Source: Own compilation from PISA 2006 database

Table 11: Stochastic Distance Function for GDPS in Castile-Leon

Variables	*Coeff.*	*Std. Dev*	*p-value*	*Variables*	*Coeff.*	*Std. Dev.*	*p-value*
Intercept	**-0.201**	0.025	0.000	$(Lnx_1)^2$	-0.028	0.085	0.754
Outputs				$(Lnx_2)^2$	-0.497	0.400	0.282
Lny_1 (*math score*)	*0.303*			$(Lnx_3)^2$	1.336	3.512	0.536
Lny_2 (*reading score*)	**0.311**	0.071	0.000	$(Lnx_4)^2$	-0.027	0.276	0.749
Lny_3 (*science score*)	**0.386**	0.090	0.000	$(Lnx_1)(Lnx_2)$	-0.100	0.087	0.264
$(Lny_1)^2$	*4.603*			$(Lnx_1)(Lnx_3)$	-0.202	0.477	0.698
$(Lny_2)^2$	**2.889**	0.793	0.002	$(Lnx_1)(Lnx_4)$	-0.044	0.142	0.773
$(Lny_3)^2$	**4.649**	1.272	0.003	$(Lnx_2)(Lnx_3)$	0.174	0.606	0.522
$(Lny_1)(Lny_2)$	*-1.422*			$(Lnx_2)(Lnx_4)$	-0.159	0.136	0.305
$(Lny_1)(Lny_3)$	*-3.181*			$(Lnx_3)(Lnx_4)$	0.441	0.804	0.369
$(Lny_2)(Lny_3)$	-1.468	0.780	0.145	***Input-output***			
Inputs				$(Lnx_1)(Lny_1)$	*0.214*		
Lnx_1 (*Scmatedu*)	0.017	0.023	0.499	$(Lnx_1)(Lny_2)$	0.045	0.149	0.629
Lnx_2 (*Ecsc*)	**-0.150**	0.041	0.000	$(Lnx_1)(Lny_3)$	-0.103	0.180	0.465
Lnx_3 (*Peer*)	-0.234	0.294	0.433	$(Lnx_2)(Lny_1)$	*-1.253*		
Lnx_4 (*Pcgirls*)	-0.104	0.060	0.116	$(Lnx_2)(Lny_2)$	**0.994**	0.387	0.047
x_5 (*Repone*)	**0.127**	0.012	0.000	$(Lnx_2)(Lny_3)$	0.259	0.468	0.398
x_6 (*Repmore*)	**0.199**	0.023	0.000	$(Lnx_3)(Lny_1)$	*1.821*		
Lnx_7 (*Stratio*)	-0.022	0.043	0.670	$(Lnx_3)(Lny_2)$	-0.693	0.996	0.437
Lnx_8 (*Schsize*)	0.014	0.013	0.317	$(Lnx_3)(Lny_3)$	-1.128	1.220	0.450
x_9 (*Firstgen*)	**0.087**	0.030	0.012	$(Lnx_4)(Lny_1)$	*0.400*		
x_{10} (*Secgen*)	*omitted*	*(omitted)*	*(omitted)*	$(Lnx_4)(Lny_2)$	0.154	0.256	0.602
x_{11} (*Gender*)	**0.019**	0.010	0.083	$(Lnx_4)(Lny_3)$	**-0.555**	0.282	0.066
Sigma-v	**-5.726**	0.292	0.000	*Mean Eff.*	0.896	0.060	
Sigma-u	**-3.960**	0.194	0.000	*N*	458		

Source: Own compilation from PISA 2006 database

Table 12: Stochastic Distance Function for PS in Castile-Leon

Variables	*Coeff.*	*Std. Dev*	*p-value*	*Variables*	*Coeff.*	*Std. Dev.*	*p-value*
Intercept	**-0.167**	0.019	0.000	x_6 (*Repmore*)	**0.219**	0.018	0.000
Outputs				Lnx_7 (*Stratio*)	**-0.126**	0.040	0.002
Lny_1 (*math score*)	*0.234*			Lnx_8 (*Schsize*)	**-0.027**	0.014	0.055
Lny_2 (*reading score*)	**0.353**	0.043	0.000	x_9 (*Firstgen*)	**0.059**	0.025	0.024
Lny_3 (*science score*)	**0.414**	0.052	0.000	x_{10} (*Secgen*)	0.029	0.113	0.672
$(Lny_1)^2$	*3.233*			x_{11} (*Gender*)	0.015	0.008	0.091
$(Lny_2)^2$	**2.667**	0.450	0.000	$(Lnx_1)^2$	-0.042	0.098	0.651
$(Lny_3)^2$	**4.637**	0.801	0.000	$(Lnx_2)^2$	-0.082	0.241	0.735
$(Lny_1)(Lny_2)$	*-0.632*			$(Lnx_3)^2$	-0.077	2.006	0.700
$(Lny_1)(Lny_3)$	*-2.601*			$(Lnx_4)^2$	0.187	0.450	0.672
$(Lny_2)(Lny_3)$	**-2.035**	0.510	0.001	$(Lnx_1)(Lnx_2)$	-0.009	0.077	0.665
Inputs				$(Lnx_1)(Lnx_3)$	0.074	0.278	0.721
Lnx_1 (*Scmatedu*)	-0.004	0.024	0.640	$(Lnx_1)(Lnx_4)$	0.060	0.122	0.632
Lnx_2 (*Ecsc*)	-0.049	0.029	0.111	$(Lnx_2)(Lnx_3)$	-0.123	0.457	0.722
Lnx_3 (*Peer*)	**-0.373**	0.087	0.000	$(Lnx_2)(Lnx_4)$	0.026	0.175	0.708
Lnx_4 (*Pcgirls*)	-0.052	0.051	0.365	$(Lnx_3)(Lnx_4)$	-1.091	0.709	0.188
x_5 (*Repone*)	**0.137**	0.009	0.000				
Sigma-v	**-4.859**	0.034	0.000	*Mean Eff.*	0.903	0.046	
Sigma-u	**-4.118**	0.043	0.000	*N*	902		

Source: Own compilation from PISA 2006 database

Table 13: Stochastic Distance Function for GDPS in Catalonia

Variables	***Coeff.***	***Std. Dev***	***p-value***	***Variables***	***Coeff.***	***Std. Dev.***	***p-value***
Intercept	-0.134	0.295	0.465	$(Lnx_1)^2$	-1.457	1.280	0.315
Outputs				$(Lnx_2)^2$	0.036	0.493	0.774
Lny_1 (*math score*)	*0.514*			$(Lnx_3)^2$	-12.981	96.205	0.621
Lny_2 (*reading score*)	**0.311**	0.102	0.009	$(Lnx_4)^2$	9.416	16.895	0.541
Lny_3 (*science score*)	0.175	0.124	0.357	$(Lnx_1)(Lnx_2)$	-0.132	0.164	0.504
$(Lny_1)^2$	*3.415*			$(Lnx_1)(Lnx_3)$	2.945	2.302	0.270
$(Lny_2)^2$	**1.235**	0.206	0.000	$(Lnx_1)(Lnx_4)$	-3.904	4.905	0.463
$(Lny_3)^2$	**4.129**	0.920	0.000	$(Lnx_2)(Lnx_3)$	2.429	1.322	0.091
$(Lny_1)(Lny_2)$	*-0.261*			$(Lnx_2)(Lnx_4)$	-0.248	0.615	0.480
$(Lny_1)(Lny_3)$	*-3.154*			$(Lnx_3)(Lnx_4)$	*omitted*	*omitted*	*omitted*
$(Lny_2)(Lny_3)$	**-0.974**	0.502	0.060	***Input-output***			
Inputs				$(Lnx_1)(Lny_1)$	*-0.033*		
Lnx_1 (*Scmatedu*)	-0.241	0.208	0.334	$(Lnx_1)(Lny_2)$	-0.007	0.238	0.445
Lnx_2 (*Ecsc*)	**-0.184**	0.069	0.012	$(Lnx_1)(Lny_3)$	0.040	0.332	0.497
Lnx_3 (*Peer*)	-0.310	3.302	0.708	$(Lnx_2)(Lny_1)$	*0.417*		
Lnx_4 (*Pcgirls*)	-0.314	1.448	0.590	$(Lnx_2)(Lny_2)$	0.174	0.374	0.382
x_5 (*Repone*)	**0.132**	0.016	0.000	$(Lnx_2)(Lny_3)$	-0.591	0.467	0.279
x_6 (*Repmore*)	**0.292**	0.054	0.000	$(Lnx_3)(Lny_1)$	*-0.535*		
Lnx_7 (*Stratio*)	0.190	0.728	0.781	$(Lnx_3)(Lny_2)$	0.303	1.737	0.320
Lnx_8 (*Schsize*)	0.003	0.109	0.666	$(Lnx_3)(Lny_3)$	0.232	2.257	0.535
x_9 (*Firstgen*)	0.017	0.032	0.637	$(Lnx_4)(Lny_1)$	*1.785*		
x_{10} (*Secgen*)	0.061	0.058	0.270	$(Lnx_4)(Lny_2)$	-1.496	0.959	0.137
x_{11} (*Gender*)	0.025	0.014	0.106	$(Lnx_4)(Lny_3)$	-0.289	1.170	0.683
Sigma-v	**-5.363**	0.308	0.000	*Mean Eff.*	0.892	0.061	
Sigma-u	**-3.890**	0.267	0.000	*N*	328		

Source: Own compilation from PISA 2006 database

Table 14: Stochastic Distance Function for PS in Catalonia

Variables	*Coeff.*	*Std. Dev*	*p-value*	*Variables*	*Coeff.*	*Std. Dev.*	*p-value*
Intercept	**-0.246**	0.015	0.000	$(Lnx_1)^2$	-0.012	0.052	0.768
Outputs				$(Lnx_2)^2$	0.002	0.271	0.715
Lny_1 (*math score*)	*0.538*			$(Lnx_3)^2$	-1.942	2.782	0.487
Lny_2 (*reading score*)	**0.316**	0.043	0.000	$(Lnx_4)^2$	1.425	0.873	0.152
Lny_3 (*science score*)	**0.146**	0.054	0.011	$(Lnx_1)(Lnx_2)$	0.008	0.074	0.543
$(Lny_1)^2$	*3.475*			$(Lnx_1)(Lnx_3)$	-0.226	0.307	0.485
$(Lny_2)^2$	**2.815**	0.345	0.000	$(Lnx_1)(Lnx_4)$	0.333	0.287	0.291
$(Lny_3)^2$	**4.447**	0.661	0.000	$(Lnx_2)(Lnx_3)$	-0.503	0.564	0.380
$(Lny_1)(Lny_2)$	*-0.921*			$(Lnx_2)(Lnx_4)$	-0.102	0.326	0.529
$(Lny_1)(Lny_3)$	*-2.553*			$(Lnx_3)(Lnx_4)$	0.526	1.085	0.627
$(Lny_2)(Lny_3)$	**-1.894**	0.405	0.000	***Input-output***			
Inputs				$(Lnx_1)(Lny_1)$	*-0.091*		
Lnx_1 (*Scmatedu*)	-0.016	0.016	0.313	$(Lnx_1)(Lny_2)$	-0.092	0.106	0.464
Lnx_2 (*Ecsc*)	**-0.122**	0.031	0.000	$(Lnx_1)(Lny_3)$	0.183	0.139	0.262
Lnx_3 (*Peer*)	**-0.292**	0.127	0.022	$(Lnx_2)(Lny_1)$	*-0.343*		
Lnx_4 (*Pcgirls*)	**0.159**	0.077	0.061	$(Lnx_2)(Lny_2)$	0.232	0.227	0.329
x_5 (*Repone*)	**0.154**	0.011	0.000	$(Lnx_2)(Lny_3)$	0.111	0.289	0.764
x_6 (*Repmore*)	**0.239**	0.027	0.000	$(Lnx_3)(Lny_1)$	*0.108*		
Lnx_7 (*Stratio*)	0.106	0.073	0.175	$(Lnx_3)(Lny_2)$	0.282	0.674	0.595
Lnx_8 (*Schsize*)	0.027	0.022	0.237	$(Lnx_3)(Lny_3)$	-0.391	0.919	0.584
x_9 (*Firstgen*)	**0.072**	0.019	0.001	$(Lnx_4)(Lny_1)$	*1.345*		
x_{10} (*Secgen*)	0.012	0.050	0.701	$(Lnx_4)(Lny_2)$	-0.659	0.421	0.152
x_{11} (*Gender*)	0.016	0.009	0.113	$(Lnx_4)(Lny_3)$	-0.685	0.561	0.334
Sigma-v	**-5.145**	0.179	0.000	*Mean Eff.*	0.874	0.071	
Sigma-u	**-3.529**	0.135	0.000	*N*	773		

Source: Own compilation from PISA 2006 database

Table 15: Stochastic Distance Function for GDPS in Galicia[58]

Variables	*Coeff.*	*Std. Dev*	*p-value*	*Variables*	*Coeff.*	*Std. Dev.*	*p-value*
Intercept	**-0.243**	0.038	0.000	Lnx$_3$ (*Peer*)	-0.833	0.553	0.171
Outputs				Lnx$_4$ (*Pcgirls*)	-0.068	0.115	0.624
Lny$_1$ (*math score*)	*0.625*			x$_5$ (*Repone*)	**0.126**	0.018	0.000
Lny$_2$ (*reading score*)	0.133	0.073	0.093	x$_6$ (*Repmore*)	**0.231**	0.028	0.000
Lny$_3$ (*science score*)	**0.242**	0.089	0.015	Lnx$_7$ (*Stratio*)	-0.093	0.063	0.210
(Lny$_1$)^2	*3.490*			Lnx$_8$ (*Schsize*)	-0.014	0.021	0.547
(Lny$_2$)^2	1.037	0.605	0.094	x$_9$ (*Firstgen*)	-0.162	0.120	0.200
(Lny$_3$)^2	0.695	0.991	0.509	x$_{10}$ (*Secgen*)	0.007	0.052	0.799
(Lny$_1$)(Lny$_2$)	*-1.916*			x$_{11}$ (*Gender*)	**0.051**	0.015	0.001
(Lny$_1$)(Lny$_3$)	*-1.574*			(Lnx$_1$)^2	0.275	0.187	0.150
(Lny$_2$)(Lny$_3$)	0.879	0.613	0.226	(Lnx$_2$)^2	-0.259	0.471	0.611
Inputs				(Lnx$_3$)^2	0.944	10.292	0.757
Lnx$_1$ (*Scmatedu*)	0.106	0.070	0.139	(Lnx$_4$)^2	1.167	1.640	0.367
Lnx$_2$ (*Ecsc*)	-0.096	0.057	0.099				
Sigma-v	**-5.390**	0.310	0.000	*Mean Eff.*	0.888	0.069	
Sigma-u	**-3.858**	0.226	0.000	*N*	296		

Source: Own compilation from PISA 2006 database

Table 16: Stochastic Distance Function for PS in Galicia

Variables	*Coeff.*	*Std. Dev*	*p-value*	*Variables*	*Coeff.*	*Std. Dev.*	*p-value*
Intercept	**-0.208**	0.013	0.000	x$_6$ (*Repmore*)	**0.268**	0.012	0.000
Outputs				Lnx$_7$ (*Stratio*)	**0.011**	0.023	0.650
Lny$_1$ (*math score*)	*0.406*			Lnx$_8$ (*Schsize*)	0.002	0.012	0.789
Lny$_2$ (*reading score*)	**0.327**	0.032	0.000	x$_9$ (*Firstgen*)	-0.001	0.027	0.661
Lny$_3$ (*science score*)	**0.267**	0.041	0.000	x$_{10}$ (*Secgen*)	0.078	0.047	0.101
(Lny$_1$)^2	*3.024*			x$_{11}$ (*Gender*)	**0.021**	0.008	0.015
(Lny$_2$)^2	**1.481**	0.190	0.000	(Lnx$_1$)^2	0.073	0.049	0.142
(Lny$_3$)^2	**2.611**	0.484	0.000	(Lnx$_2$)^2	0.053	0.213	0.658
(Lny$_1$)(Lny$_2$)	*-0.947*			(Lnx$_3$)^2	-0.381	1.376	0.785
(Lny$_1$)(Lny$_3$)	*-2.077*			(Lnx$_4$)^2	**-0.257**	0.080	0.003
(Lny$_2$)(Lny$_3$)	**-0.534**	0.236	0.060	(Lnx$_1$)(Lnx$_2$)	0.101	0.058	0.109
Inputs				(Lnx$_1$)(Lnx$_3$)	-0.079	0.218	0.719
Lnx$_1$ (*Scmatedu*)	-0.001	0.015	0.765	(Lnx$_1$)(Lnx$_4$)	**-0.218**	0.096	0.033
Lnx$_2$ (*Ecsc*)	**-0.106**	0.024	0.000	(Lnx$_2$)(Lnx$_3$)	0.281	0.346	0.369
Lnx$_3$ (*Peer*)	-0.108	0.072	0.157	(Lnx$_2$)(Lnx$_4$)	-0.076	0.074	0.316
Lnx$_4$ (*Pcgirls*)	-0.038	0.041	0.378	(Lnx$_3$)(Lnx$_4$)	0.357	0.662	0.615
x$_5$ (*Repone*)	**0.143**	0.008	0.000				
Sigma-v	**-4.882**	0.129	0.000	*Mean Eff.*	0.903	0.047	
Sigma-u	**-4.122**	0.187	0.000	*N*	1,084		

Source: Own compilation from PISA 2006 database

[58] We estimate a quadratic functional form for GDPS in Galicia, so the tranlog specification does not converge.

Table 17: Stochastic Distance Function for GDPS in Navarre

Variables	*Coeff.*	*Std. Dev*	*p-value*	*Variables*	*Coeff.*	*Std. Dev.*	*p-value*
Intercept	**-0.149**	0.019	0.000	$(Lnx_1)^2$	0.012	0.170	0.803
Outputs				$(Lnx_2)^2$	-0.348	0.328	0.302
Lny_1 (*math score*)	*0.379*			$(Lnx_3)^2$	**-3.610**	1.636	0.049
Lny_2 (*reading score*)	**0.514**	0.056	0.000	$(Lnx_4)^2$	**-0.159**	0.039	0.000
Lny_3 (*science score*)	0.107	0.069	0.142	$(Lnx_1)(Lnx_2)$	0.103	0.108	0.353
$(Lny_1)^2$	*1.671*			$(Lnx_1)(Lnx_3)$	-0.237	0.224	0.315
$(Lny_2)^2$	**2.999**	0.422	0.000	$(Lnx_1)(Lnx_4)$	**-0.446**	0.195	0.046
$(Lny_3)^2$	**2.865**	0.722	0.004	$(Lnx_2)(Lnx_3)$	0.647	0.537	0.267
$(Lny_1)(Lny_2)$	*-0.902*			$(Lnx_2)(Lnx_4)$	0.004	0.043	0.726
$(Lny_1)(Lny_3)$	*-0.768*			$(Lnx_3)(Lnx_4)$	0.112	0.383	0.770
$(Lny_2)(Lny_3)$	**-2.096**	0.472	0.000	***Input-output***			
Inputs				$(Lnx_1)(Lny_1)$	*-0.045*		
Lnx_1 (*Scmatedu*)	0.066	0.033	0.051	$(Lnx_1)(Lny_2)$	-0.125	0.131	0.323
Lnx_2 (*Ecsc*)	**-0.113**	0.042	0.013	$(Lnx_1)(Lny_3)$	0.170	0.184	0.371
Lnx_3 (*Peer*)	0.027	0.129	0.773	$(Lnx_2)(Lny_1)$	*0.441*		
Lnx_4 (*Pcgirls*)	**-0.306**	0.085	0.001	$(Lnx_2)(Lny_2)$	0.292	0.291	0.361
x_5 (*Repone*)	**0.167**	0.012	0.000	$(Lnx_2)(Lny_3)$	-0.733	0.407	0.200
x_6 (*Repmore*)	**0.272**	0.027	0.000	$(Lnx_3)(Lny_1)$	*-0.680*		
Lnx_7 (*Stratio*)	0.007	0.032	0.808	$(Lnx_3)(Lny_2)$	0.027	0.599	0.769
Lnx_8 (*Schsize*)	0.007	0.011	0.578	$(Lnx_3)(Lny_3)$	0.653	0.806	0.474
x_9 (*Firstgen*)	-0.016	0.022	0.482	$(Lnx_4)(Lny_1)$	*-0.121*		
x_{10} (*Secgen*)	-0.042	0.058	0.541	$(Lnx_4)(Lny_2)$	**0.191**	0.061	0.033
x_{11} (*Gender*)	-0.006	0.010	0.579	$(Lnx_4)(Lny_3)$	-0.070	0.108	0.472
Sigma-v	**-5.360**	0.183	0.000	*Mean Eff.*	0.904	0.052	
Sigma-u	**-4.128**	0.182	0.000	*N*	605		

Source: Own compilation from PISA 2006 database

Table 18: Stochastic Distance Function for PS in Navarre

Variables	***Coeff.***	***Std. Dev***	***p-value***	***Variables***	***Coeff.***	***Std. Dev.***	***p-value***
Intercept	**-0.169**	0.018	0.000	x_6 (*Repmore*)	**0.260**	0.024	0.000
Outputs				Lnx_7 (*Stratio*)	**0.122**	0.050	0.036
Lny_1 (*math score*)	*0.473*			Lnx_8 (*Schsize*)	0.001	0.012	0.710
Lny_2 (*reading score*)	**0.460**	0.040	0.000	x_9 (*Firstgen*)	0.010	0.018	0.595
Lny_3 (*science score*)	0.067	0.051	0.244	x_{10} (*Secgen*)	0.039	0.078	0.565
$(Lny_1)^2$	*3.220*			x_{11} (*Gender*)	-0.005	0.009	0.539
$(Lny_2)^2$	**2.906**	0.323	0.000	$(Lnx_1)^2$	**-0.199**	0.063	0.001
$(Lny_3)^2$	**4.728**	0.562	0.000	$(Lnx_2)^2$	-0.097	0.256	0.706
$(Lny_1)(Lny_2)$	*-0.699*			$(Lnx_3)^2$	-2.964	3.075	0.565
$(Lny_1)(Lny_3)$	*-2.521*			$(Lnx_4)^2$	-1.134	0.884	0.228
$(Lny_2)(Lny_3)$	**-2.207**	0.325	0.000	$(Lnx_1)(Lnx_2)$	-0.105	0.073	0.202
Inputs				$(Lnx_1)(Lnx_3)$	0.316	0.357	0.231
Lnx_1 (*Scmatedu*)	0.002	0.027	0.476	$(Lnx_1)(Lnx_4)$	0.059	0.128	0.615
Lnx_2 (*Ecsc*)	-0.080	0.044	0.139	$(Lnx_2)(Lnx_3)$	0.880	0.603	0.208
Lnx_3 (*Peer*)	0.057	0.199	0.577	$(Lnx_2)(Lnx_4)$	0.511	0.294	0.107
Lnx_4 (*Pcgirls*)	-0.121	0.106	0.297	$(Lnx_3)(Lnx_4)$	-3.567	1.279	0.011
x_5 (*Repone*)	**0.159**	0.011	0.000				
Sigma-v	**-4.757**	0.114	0.000	*Mean Eff.*	0.892	0.053	
Sigma-u	**-3.905**	0.114	0.000	*N*	877		

Source: Own compilation from PISA 2006 database

Table 19: Stochastic Distance Function for GDPS in Rioja

Variables	***Coeff.***	***Std. Dev***	***p-value***	***Variables***	***Coeff.***	***Std. Dev.***	***p-value***
Intercept	**-0.153**	0.027	0.000	x_6 (*Repmore*)	**0.172**	0.026	0.000
Outputs				Lnx_7 (*Stratio*)	**0.144**	0.068	0.041
Lny_1 (*math score*)	*0.384*			Lnx_8 (*Schsize*)	**0.037**	0.019	0.062
Lny_2 (*reading score*)	**0.417**	0.046	0.000	x_9 (*Firstgen*)	-0.009	0.027	0.628
Lny_3 (*science score*)	**0.199**	0.057	0.001	x_{10} (*Secgen*)	*omitted*	*omitted*	*omitted*
$(Lny_1)^2$	*2.407*			x_{11} (*Gender*)	-0.016	0.011	0.159
$(Lny_2)^2$	**2.594**	0.383	0.000	$(Lnx_1)^2$	0.083	0.071	0.260
$(Lny_3)^2$	**4.062**	0.684	0.000	$(Lnx_2)^2$	**0.995**	0.349	0.007
$(Lny_1)(Lny_2)$	*-0.469*			$(Lnx_3)^2$	**5.383**	2.304	0.029
$(Lny_1)(Lny_3)$	*-1.938*			$(Lnx_4)^2$	**2.693**	0.759	0.000
$(Lny_2)(Lny_3)$	**-2.125**	0.500	0.000	$(Lnx_1)(Lnx_2)$	-0.045	0.092	0.635
Inputs				$(Lnx_1)(Lnx_3)$	0.171	0.261	0.560
Lnx_1 (*Scmatedu*)	**0.089**	0.022	0.000	$(Lnx_1)(Lnx_4)$	-0.201	0.281	0.507
Lnx_2 (*Ecsc*)	**-0.125**	0.039	0.002	$(Lnx_2)(Lnx_3)$	-1.026	0.562	0.087
Lnx_3 (*Peer*)	**-0.351**	0.197	0.079	$(Lnx_2)(Lnx_4)$	-0.125	0.253	0.624
Lnx_4 (*Pcgirls*)	**0.140**	0.105	0.215	$(Lnx_3)(Lnx_4)$	-1.459	1.078	0.209
x_5 (*Repone*)	**0.121**	0.012	0.000				
Sigma-v	**-5.482**	0.203	0.000	*Mean Eff.*	0.892	0.062	
Sigma-u	**-3.859**	0.152	0.000	*N*	563		

Source: Own compilation from PISA 2006 database

Table 20: Stochastic Distance Function for PS in Rioja

Variables	***Coeff.***	***Std. Dev***	***p-value***	***Variables***	***Coeff.***	***Std. Dev.***	***p-value***
Intercept	**-0.131**	0.022	0.000	x_6 (*Repmore*)	**0.202**	0.022	0.000
<u>*Outputs*</u>				Lnx_7 (*Stratio*)	-0.071	0.054	0.244
Lny_1 (*math score*)	<u>*0.402*</u>			Lnx_8 (*Schsize*)	**-0.046**	0.014	0.002
Lny_2 (*reading score*)	**0.399**	0.041	0.000	x_9 (*Firstgen*)	**0.075**	0.018	0.000
Lny_3 (*science score*)	**0.199**	0.055	0.000	x_{10} (*Secgen*)	0.031	0.055	0.586
$(Lny_1)^2$	<u>*4.347*</u>			x_{11} (*Gender*)	0.002	0.009	0.754
$(Lny_2)^2$	**1.868**	0.341	0.000	$(Lnx_1)^2$	**-0.236**	0.063	0.001
$(Lny_3)^2$	**2.713**	0.533	0.000	$(Lnx_2)^2$	0.221	0.292	0.472
$(Lny_1)(Lny_2)$	<u>*-1.751*</u>			$(Lnx_3)^2$	**-17.997**	4.142	0.000
$(Lny_1)(Lny_3)$	<u>*-2.596*</u>			$(Lnx_4)^2$	-7.889	4.764	0.105
$(Lny_2)(Lny_3)$	-0.117	0.342	0.532	$(Lnx_1)(Lnx_2)$	-0.044	0.077	0.545
<u>*Inputs*</u>				$(Lnx_1)(Lnx_3)$	**-2.785**	0.597	0.000
Lnx_1 (*Scmatedu*)	**-0.053**	0.024	0.034	$(Lnx_1)(Lnx_4)$	-0.630	0.387	0.112
Lnx_2 (*Ecsc*)	-0.060	0.037	0.129	$(Lnx_2)(Lnx_3)$	0.713	0.650	0.284
Lnx_3 (*Peer*)	0.093	0.252	0.707	$(Lnx_2)(Lnx_4)$	0.465	0.571	0.463
Lnx_4 (*Pcgirls*)	-0.014	0.136	0.730	$(Lnx_3)(Lnx_4)$	-0.030	2.473	0.733
x_5 (*Repone*)	**0.155**	0.010	0.000				
Sigma-v	**-5.267**	0.179	0.000	*Mean Eff.*	0.890	0.061	
Sigma-u	**-3.829**	0.152	0.000	*N*	676		

Source: Own compilation from PISA 2006 database

CAPÍTULO 3

"Comparing public and government-dependent private school management through a new Educational Malmquist index approach"

1. INTRODUCTION

One of the main goals in the field of the economics of education is to analyze the inefficiency behaviors in the learning process. The sources of inefficiency may be due to multiple reasons such as the way in which the resources are organized and managed, the motivation of the agents involved in the learning process or the structure itself of the educational system (*Nechyva* 2000; *Woessman* 2001).

In order to tackle the inefficiency measurement issue in education many studies have used the non parametric Data Envelopment Analysis (*Bessent and Bessent* 1980; *Charnes, Cooper and Rhodes* 1981 and *Bessent et al.* 1982[59]) and other parametric methodologies (*Christensen, Jorgenson and Lau* 1971; *Gyimah-Brempong and Gyapong* 1992; *Deller and Rudnicki* 1993; *Grosskopf et al.* 1997; *Cordero et al.* 2010b; *Perelman and Santín* 2011).

The recently increase of national and international programs to evaluate the scholar achievement during last decades shows the higher policy concern about educational performance. Hence, last years, some international projects have been developed in order to evaluate the educational achievements in which are considered the vehicular disciplines: Science, Mathematics and Lecture. The most important international programs are TIMSS (*Third International Mathematics and Science Study*), PISA (*Programme for International Student Assessment*) and PIRLS (*Progress in International Reading Literacy Study*), although many countries perform their own evaluations *e.g.* the *National Assessment of Educational Progress* (NAEP) in the United States.

The main advantage of these programs is that provide an external evaluation of the educational results with the aim of identifying the causes of the school failure allowing to policy makers and school principals to go into their management strengths and weakness in depth. However, the comparison of the student or the school behaviors along the time using these international studies is not possible due to the participant schools and students differ from one wave to another.

In this paper, we propose a new approach to measure productivity when only a pseudo-panel data is available. Traditionally, Malmquist index proposed by *Caves et al.* (1982) represents productivity changes between two periods which imply the same unit is observed in both periods. However, this approach does not allow for detecting productivity disparities among units whose management structure is not the same within a period. Consequently,

[59] For an empirical survey of frontier efficiency techniques in education, see *Worthington* (2001).

relevant information to planning policy maker strategies are omitted which may lead to non accessible goals could be demanded in some cases or may be penalized unfairly.

The purpose of our study is to analyze productivity differences among publicly financed schools using the Malmquist index approach. A similar strategy was developed by *Berg et al.* (1993)[60] with the aim of comparing banking efficiencies in three Nordic countries or *Balk and Althin* (1996) to compare Swedish pharmacies productivity evolution over the period 1980-1989. Both papers propose a new approach to calculate the Malmquist index, taking a particular unit as the comparison reference or taking a fix period as reference in order to calculate multi-period Malmquist indices, respectively, being satisfied each alternative the transitivity property.

This study attempts to analyze the main divergences in the publicly finance educational system in Spain taking into account the different background, not only the scholar resource capacity either the familiar and personal students' characteristics vary from one school type to another, depending on the school ownership. Thus, a non-parametric Educational Malmquist is proposed in order to measure productivity divergences between Public Schools (*PS*) and Government-Dependent Private Schools (*GDPS*) within the same period due to the organizational and management guidelines differ depending on the school ownership.

With the aim of showing our proposal potential we include an empirical application in the educational framework in order to test possible productivity disparities between *PS* and *GDPS* in three time periods (2003-2009). Analogously, the mean relative evolution behavior for both school types within 2003-2009 is analyzed to obtain a general overview of the public educational system in Spain. Hence, three Spanish regions- Basque Country, Castile-Leon and Catalonia - which participate with extended sample in the *Programme for International Student Assessment* (PISA), implemented in 2003, 2006 and 2009 by the Organization for Economic Cooperation and Development (OECD) are analyzed.

The paper is organized as follows. Section 2 provides an overview about the Malmquist index methodology jointly with our estimation strategy for a new Educational Malmquist index. Moreover, we propose four different alternatives to match both school type samples for each considered period and finally, we present the *Simar and Wilson* (1999) approach to calculate the confidence intervals for the productivity indices and their components. In Section 3 the data set and the selected inputs and outputs are described. Section 4 provides the results after applying

[60] Also see *Forsund* (2002).

our strategy and a discussion of our empirical analysis. The final section offers some conclusions and the future lines for research.

2. METHODOLOGY

Malmquist index was proposed by *Caves, Christensen and Diewet* (1982) with the aim of measuring the productivity changes within two time periods as the distance between a decision making unit (*DMU*) and the frontier for each period[61]. The index is built using different Data Envelopment Analysis (*DEA*) programs, so no assumptions, beyond monotonicity and convexity, about the production technology are required. Hence, it is especially attractive in the educational context, where multiple inputs and output are involved in the learning process and the prices are unknown or difficult to estimate.

To formalize the index we, firstly, assume constant returns to scale (*CRS*)[62], so the school's size across the time are quite similar for each region. Defining a vector of inputs $x = (x_1, \ldots, x_K) \in \Re^{K+}$ and a vector of outputs $y = (y_1, \ldots, y_M) \in \Re^{M+}$, a feasible multi-input and multi-output production technology for a period of time t $(t = 1....,T)$ can be defined using the output possibility set $P^t(x^t)$. This output possibility set can be produced using the input vector x^t: $P^t(x^t) = \{y^t: x^t \text{ can produce } y^t\}$, which is assumed to satisfy the set of axioms described in *Färe and Primont* (1995). This technology can be also defined as the output distance function proposed by *Shephard* (1970):

$$D^t\left(x^t, y^t\right) = \inf\left\{\theta : \theta > 0, \left(x^t, y^t/\theta\right) \in P^t\left(x^t\right)\right\} \tag{1}$$

From Equation (1)[63], if $D^t\left(x^t, y^t\right) < 1$ then $\left(y^t\right)$ belongs to the production set P^t (x^t) and, additionally, when $D^t\left(x^t, y^t\right) < 1$ y^t is located behind the outer boundary of the output possibility set and it is considered inefficient. Then an output-oriented period t Malmquist productivity index is:

$$M_i^t\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \frac{D_i^t(x^{t+1}, y^{t+1})}{D_i^t(x^t, y^t)} \tag{2}$$

[61] This is the most used approach, nevertheless the authors pointed out the possibility of using this index to analyze two different units for an specific period of time.

[62] There are other studies that consider CRS such as *Balk and Althin* (1996), *Ray and Desli*, (1997), *Forsund* (2002)

[63] Note that the CCR efficiency score with output orientation is just the inverse of the optimum from Equation 1.

Following *Färe et al.* (1994) we may define the Malmquist productivity index from the distance function, D^t, and the inputs - outputs endowments, x^t and y^t, for each period of time *t* *(t = 1....,T)*. The analytical expression of the index would be:

$$M\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} * \left[\left(\frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})}\right)\left(\frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)}\right)\right]^{1/2} = TEC * TC \qquad (3)$$

where a higher (lower) than one index implies productivity improvements (losses)[64].

Furthermore, Equation (3) may be decomposed into two components. The first item reflects the technical efficiency change (*TEC*), which catches the improvements (reductions) on the efficiency in period *t+1* if *TEC* > 1 (TEC < 1), whereas *TEC* = 1 indicates no changes on the technical efficiency. The second one represents the technological change (*TC*) in period *t+1*, whose sign may be analyzed in a similar way than *TEC,* although both measures may have different directions.

The Malmquist index methodology consists of observing a *DMU* in different periods, which requires a panel database to be implemented; or, even, to observe two different DMU within the same period of time. However this approach does not allow deepening on the potential disparities among different units whose organizational structure and background circumstances vary across the time. It is the case of publicly finance educational system in Spain, where both *PS* and *GDPS* are publicly financed but they are managed by a public education authority and a private agency, respectively, so different school performance may due to organizational divergences among them.

Thus, a non-parametric Educational Malmquist is built in order to achieve an average indicator of the productivity divergences between public and government-dependent private schools within a period when the organizational and management guidelines differ depending on the school ownership. Hence, a pseudo-panel database as *PISA* or *TIMSS* is required for a correct implementation of this methodology, which guarantees both school types' samples are representative from the public and the government-dependent private educational systems.

[64] This productivity index is the geometric mean of two productivity index, where the first one takes the period *t* as reference and the second one the period *t+1*, avoiding the arbitrary selection of the referential period.

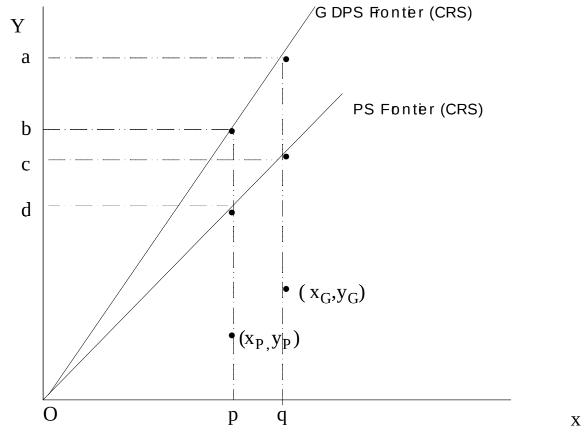
The expression for the Educational Malmquist[65] may be easily obtained by replacing the super-indices *t* and *t+1* by *G* and *P*, which indicate the government-dependent private and public schools, respectively.

$$\mathrm{EM} = \frac{\mathrm{D}^G(\mathrm{x}^G, \mathrm{y}^G)}{\mathrm{D}^\mathrm{P}(\mathrm{x}^\mathrm{P}, \mathrm{y}^\mathrm{P})} \cdot \left[\left(\frac{D^G(x^P, y^P)}{D^P(x^P, y^P)} \right) \cdot \left(\frac{D^G(x^G, y^G)}{D^P(x^G, y^G)} \right) \right]^{1/2} \tag{4}$$

Equation (4) shows the average productivity differences between both *PS* and *GDPS* in one year as a result of the efficiency and the technological gap between both school types. Linear programming is implemented in order to achieve the average distances of each school type to its own frontier. With that purpose, we estimate the distance of each school to its own frontier and then all these measures are expressed into the average one within the whole set of units each case. Thus, this approach do not allow for evaluating specific school behavior either only the average discrepancies between both school ownership are observed. Then, if the index is higher (smaller) than one reflects that *GDPS* are in average more (less) productive than *PS*.

Figure 1 illustrates these concepts in one period. Let assume that *GDPS Frontier (CRS)* and *PS Frontier (CRS)* represent the constant returns to scale technology for both, government-dependent private schools and public ones, respectively. Moreover, the average inefficient *PS* (*GDPS*) consumes x_P (x_G) input and produces y_P, (y_G) quantity of output, being the sub-index *P* and *G* the school ownership indicator for public school (*PS*) and government-dependent private school (*GDPS*).

Figure 1: Productivity divergences between PS and GDPS



Source: Own compilation

[65] The efficiency component decomposition is not interesting in the framework of cross-sectional productivity divergences, so we do not include both the pure and the scale efficiency items in the analytical expression of the Educational Malmquist index.

Moreover, with the aim of analyzing both school ownership divergences within two periods we propose to build the ratio of two Educational Malmquist expressions in different periods. This strategy allows checking which organizational pattern present a better behavior along the time, so relevant implication for policy makers may be deducted from this analysis. The productivity change between *GDPS* and *PS* within *t* and *t+1* is as follows:

$$EMC(t,t+1)=\frac{EM_t}{EM_{t+1}} \tag{5}$$

Equation (5) indicates productivity gains for public schools when the index is higher than unity (*EMC* > 1) or productivity losses when it is lower than one (*EMC* < 1). Similarly, the efficiency change (*EC*) and the technology gap (*TG*) is built by the ratio of the efficiency (technological) difference within the two periods for each school type, as Equation (6) shows:

$$EC(t,t+1)=\frac{ED_t}{ED_{t+1}}\ ;\quad TG(t,t+1)=\frac{TD_t}{TD_{t+1}} \tag{6}$$

where ED_t (ED_{t+1}) and TD_t (TD_{t+1}) represent the efficiency and the technical divergences between *GDPS* and *PS* at the period *t* (*t+1*), respectively. A higher than one ratio implies that *PS* are, on average, more efficient and/or technologically advanced than *GDPS*.

2.1. Matching of schools' representative samples

A relevant challenge for the Educational Malmquist approach is to match two samples with different sizes. The traditional Malmquist may be estimated using unbalanced samples but it means that the average Educational Malmquist is built without the information of units unmatched, although all information available is used in order to estimate each annual frontier and to evaluate other units.

For empirical purposes, the most commonly situation is that *PS* and *GDPS* present a different sample size (*n* and *m* respectively). Therefore, the sample size for *PS* uses to be higher than *GDPS*, with the exception of Basque Country. On the other hand, our proposal consists of matching different units instead of the same unit in different time periods, so our analysis is only valid at the mean value. Hence, we propose four different alternatives to obtain robust matches. Then, we display bellow the main details of each alternative.

Alternative 1:

The Alternative 1 consists of matching samples randomly. Let assumes that $n > m$. Therefore, we select m units from the largest sample n, being the remainder units using to build the productive frontier but they are not considered to obtain the Educational Malmquist index.

Alternative 2:

The Alternative 2 consists of adding a number of units from the smaller sample to obtain the same number of units than in the largest one. Let assumes that $n > m$, then:

- If $m*2 > n$; $n - m$ units are removed randomly from the m sample to equal n.
- If $m*f > n$; where f *is* a natural number equals or higher than 2 ($f= 2, 3,\ldots, F$) and it is used to match the m sample multiplied by f.
- If $m*2 < n$; where f is a natural number equals or higher than 2 ($f= 2, 3,\ldots, F$) and it is used to match the m sample multiplied by f. Then, $n – m*f$ units are removed randomly from the original m sample to equal n.

Alternative 3:

Alternative 3 composes of the following steps:

- A Data Envelopment Analysis (*DEA*) is estimated for the higher sample.
- Let assumes that $n > m$. Then, m units are selected from the higher sample, n, maintaining the percentage of efficient units.
- Unmatched units are used to build the productive frontier and to evaluate the other units, although not to obtain the mean indices.

Alternative 4:

Alternative 4 composes of the following steps:

- A *DEA* is estimated for the smaller sample.

Let assumes that $n > m$. Thus, m units are randomly selected from the smaller sample, m, to achieve n maintaining the percentage of efficient units, then:

- If $m*2 > n$; $n - m$ units are removed randomly from the m sample to equal n.

- If $m*f > n$; where f is a natural number equals or higher than 2 ($f= 2, 3,\dots, F$) and it is used to match the m sample multiplied by f.
- If $m*2 < n$; where f is a natural number equals or higher than 2 ($f= 2, 3,\dots, F$) and it is used to match the m sample multiplied by f. Then, $n - m*f$ units are removed randomly from the original m sample to equal n.

Finally, unmatched units are used to build the productive frontier and to evaluate the other units, although not to obtain the mean indices.

2.2. Confidential Intervals

Original *Färe et al.* (1992) Malmquist index measures productivity and its components changes along the time using the ratio of two output (input) distance functions. However, this approach does not allow to test if the estimated changes in productivity and its components are actually real. On the other hand, the Malmquist index is calculated using a non-linear programming technique, as for example the Data Envelopment Analysis (DEA), so the true production frontier is actually unknown and, consequently, the results after applying this approach are not statistical supported.

Two mainly alternatives may be used in order to deal with this problem: the bootstrap estimation and the Monte Carlo experiment. Both procedures allow obtaining the confidence intervals for the Malmquist indices, although the process is different for each approach. The bootstrapping was proposed by *Simar and Wilson* (1999), who focus their strategy on the replication of the unobserved data-generating process. Nevertheless, the Monte Carlo experiment consists of obtaining a finite number of pairings, that may be balanced (Alternative 1 and Alternative 3) or unbalanced (Alternative 2 and Alternative 4), and afterward calculating a Malmquist index for each pairing. In this study, we follow the *Simar and Wilson* (1999) methodology, although a similar analysis could be done using the Monte Carlo experiment.

In order to illustrate the *Simar and Wilson* approach we assume that the production possibility setting at time t is given by the expression:

$$\mathrm{P}^t = \{(x, y) \mid x \, can \; produce \; y \; at \; time \, t\} \tag{7}$$

being x the input set and y the output one. Then, following *Shephard* (1970), the output distance function, $D_i^{G/P}$, for the unit i, which is a government-dependent private school *(GDPS)*, related to the public one *(PS)* technology, collects the normalized distance from the *i*-th unit from the *GDPS* sub-group to the boundary of the *PS*, considering the input set is fixed:

$$D_i^{G/P} \equiv \inf\left\{\theta : \theta > 0 \middle| \left(x_i^{\,G}, y_i^{\,G}/\theta\right) \in Y^P\left(x_i^{\,G}\right)\right\} \tag{8}$$

where *G* and *P* correspond to *GDPS* and *PS*, respectively, being $Y^P(x)$ the output requirement set. Thus, as Expression (3) states, the Malmquist index proposed by *Färe et al.* (1992) may be written as follows[66]:

$$M\left(x^P, y^P, x^G, y^G\right) = \frac{D^P(x^P, y^P)}{D^G(x^G, y^G)} * \left[\left(\frac{D^G(x^P, y^P)}{D^P(x^P, y^P)}\right)\left(\frac{D^G(x^G, y^G)}{D^P(x^G, y^G)}\right)\right]^{1/2} \tag{9}$$

where a higher (smaller) than one index, $M(G,P) > 1$ $\left(M(G,P) < 1\right)$, implies productivity differences in favor of government-dependent private schools (public schools) and if the index equals one, $M(G,P) = 1$, there is not productivity divergences between both school types. Therefore, the first component refers to the efficiency difference between *GDPS* and *PS* and the second one is the technological gap between both school's ownership. Similarly, values higher (smaller) than one reflect a *GDPS* advantage (disadvantage) in efficiency and in technical progress with respect to *PS*.

The estimation of the distance functions[67] may be computed solving a linear program, as Equation (10) states:

$$\left(\widehat{D}_i^{G/P}\right)^{-1} = \max\left\{\lambda \middle| x_{i,G} \le \chi^P q_i, \lambda y_{i,P} \ge Y^P q_i, q_i \in \Re_+^N\right\} \tag{10}$$

Then, the bootstrapping consists of assuming a data-generating process for Equation (14) and replicating it a large enough number *B* of pseudo-samples. Hence, for each bootstrap replication, the deviation of each unit in the original sample to the corresponding estimated frontiers is measured using *DEA* methodology, as Equation (11) shows.

$$\left(\widehat{D}_i^{G/P*}\right)^{-1} = \max\left\{\lambda \middle| x_{i,G} \le \chi^{P*} q_i, \lambda y_{i,P} \ge Y^{P*} q_i, q_i \in \Re_+^N\right\} \tag{11}$$

[66] The *Simmar and Wilson* (1999) approach is adapted to the proposed Educational Malmquist, so these expressions are equivalent to the original ones, after replacing the item *t* by *G*, indicating the government-dependent private school, and *t+1* by *P*, indicating the public school.
[67] This expression is valid for *G* (<, =, >) than *P*. See *Simar and Wilson* (1999) for a more detailed explanation.

where $Y^{G*} = \left[y^*_{1,G}, y^*_{2,G}, ..., y^*_{N,G}\right]$ and $\chi^{G*} = \left[x^*_{1,G}, x^*_{2,G}, ..., x^*_{N,G}\right]$. Afterwards, these estimates allow obtaining the bootstrap Malmquist index, $\widehat{M}_i^{*B}(G,P)$, and its components by substituting the true distance function values in Equation (9) by the respective bootstrap estimates[68].

Finally, once the bootstrap estimates are computed, the confidence intervals at the desired level of significance may be obtained approximating the unknown distribution of $\left[\widehat{M}_i(G,P) - M_i(G,P)\right]$ by $\left[\widehat{M}^*{}_i(G,P) - \widehat{M}_i(G,P)\right]$, using the bootstrap values, $\left\{\widehat{M}_i^{*B}(G,P)\right\}_{b=1}^{B}$, for an empirical estimation to the second distribution. Thus, assuming,

$$\left[\widehat{M}_i(G,P) - M_i(G,P)\right] \approx \left[\widehat{M}_i^*(G,P) - \widehat{M}_i(G,P)\right] \tag{12}$$

from Equation (12) we use the bootstrap procedure to find values, a^*_α, b^*_α, such as:

$$P\left[\left|a^*_\alpha\right| \leq \widehat{M}^*{}_i(G,P) - \widehat{M}_i(G,P) \leq \left|b^*_\alpha\right|\right] \approx 1-\alpha^{69} \tag{13}$$

After a large enough number of bootstrap replications, $B \to \infty$, we may conclude that Equation (13) yields the true values with high probability, then:

$$P\left[\left|a^*_\alpha\right| \leq \widehat{M}_i(G,P) - M_i(G,P) \leq \left|b^*_\alpha\right|\right] \approx 1-\alpha \tag{14}$$

And, finally, making some arrangements in Equation (14) such us:

$$\widehat{M}_i(G,P) + \left|a^*_\alpha\right| \leq M_i(G,P) \leq \widehat{M}_i(G,P) + \left|b^*_\alpha\right| \tag{15}$$

where the Malmquist index is significantly equal to unity, showing a productivity gap, when the interval presented in Equation (15) includes the unity and viceversa. Analogously, a similar analysis may be done for the efficiency and the technology changes, being the expressions as Equations (16-17) show, respectively:

$$\widehat{E}_i(G,P) + \left|a^*_\alpha\right| \leq E_i(G,P) \leq \widehat{E}_i(G,P) + \left|b^*_\alpha\right| \tag{16}$$

$$\widehat{T}_i(G,P) + \left|a^*_\alpha\right| \leq T_i(G,P) \leq \widehat{T}_i(G,P) + \left|b^*_\alpha\right| \tag{17}$$

[68] A more detailed explanation may be found in *Simar and Wilson* (1998).

[69] The algebraic sorting for the values and taking $((\alpha/2)\cdot 100)$ off the end of the sorted sample allow to obtain $\left|a^*_\alpha, b^*_\alpha\right|$ as the endpoints of this sorted array, where $a^*_\alpha < b^*_\alpha$.

being E_i and T_i the corresponding efficiency and technology indicators.

3. DATASET AND VARIABLES

In our empirical analysis, we use Spanish data from *PISA* 2003, 2006 and 2009 evaluation, which provide us with data from 15 years old students belonging to three regions that decided to take part in this evaluation with an extended representative sample of their population since 2003 (Basque Country, Castile-Leon and Catalonia). The methodology described in section 2 is carried out for each region separately, so Spanish regions are actually fully responsible for the management of educational resources since 2000.

One of the main advantages of the *PISA* study is that it does not evaluate cognitive abilities or skills through using one single score but each student receives a score in each test within a continuous scale. In this way, *PISA* attempts to collect the effect of the particular external conditioning factors not depending on the students when taking the test, namely being ill or becoming very nervous, among other random factors. Furthermore, it also involves that the measurement error in education is not independent from the position of the student in the distribution of results. Precisely, students with very low or high results have higher associated measurement errors and higher asymmetry in error distribution.

Likewise, *PISA* also collects an extensive dataset on these variables through two questionnaires: one completed by the students themselves and another one filled out by the principals. From these data, it is possible to extract a great amount of information referred to the main determining factors of the educational performance represented by variables associated to the familiar and the educational environments as well as to the school management and the educational supply.

Outputs and plausible values

The true output as result of an individual education is very difficult to measure empirically due to its inherent intangibility. Education does not only consist of the ability of repeating information and of answering questions, but it also involves the skills to interpret the information and to learn how to behave in the society. Unfortunately, it is really hard to measure all of them. But perhaps, according to *Hoxby* (2000), the most important reason for its consideration in the analysis 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, Readings and Sciences) as the school output. As it has already been mentioned, the study uses the concept of plausible values to measure the performance of the students, since measures in these subjects have a wide margin of error due to the fact that the measuring concept is abstract and they are subject to the special circumstances of the students on the date of the exam. The plausible values are random values obtained from the distribution function of results estimated from the student's answers in each test. They can be interpreted as a representation of the ability range for each student[70] (*Wu and Adams* 2002).

Plausible values in the three tests are used as outputs in the efficiency analysis. In order to obtain the correct results and to avoid bias problems in the estimations it is necessary to calculate five different Malmquist indices for each trio of plausible values and take the mean value afterwards, instead of using the average values to obtain one Malmquist index (*OCDE* 2005).

Inputs

In order to calculate the Malmquist index we have used four different inputs that are directly involved with the learning process *(Pared*, *Hisei*, *Schresources* and *Stratio*). *Pared* is the index of highest level of parental education, measured by the number of schooling years according to the International Standard Classification of Education (*ISCED*, *OECD*, 1999) and *Hisei* is the index of highest parental occupation status according to International Socio-economic index of Occupational Status (ISEI, *Ganzeboom et al*. 1992). *Schresources* is an index of the quality of the scholar resources derived from school principal's responses. All questionnaires contain several items related with the school deficiencies on those issues, but some items are different across the three waves. So ten coincident items were selected in each sample and the school receives one point in case the principal's response would be there is not deficient in each item[71]. The maximum (minimum) punctuation for each school is ten (zero) points, which indicates an excellent (dreadful) educational input[72]. Finally, *Stratio* is a ratio between the total number of students in the school and the total number of teachers weighted on their dedication (part-time teachers contributes 0.5 and full-time teachers 1).

[70] For a review of plausible values literature see *Mislevy et al.* (1992). For a concrete Studio of *Rasch* model and how obtain feasible values in *PISA*, see *OECD* (2005).
[71] The selected item are: 'Qualified teachers on Science', 'Qualified teachers on Mathematics', 'Qualified teachers on Lecture', 'Any other Personal Support', 'Science laboratory equipment', 'Educational material', 'Computers', 'Software', 'Library resources', 'Audiovisual resources'.
[72] This variable has been rescaled in order to avoid zeros in the empirical analysis.

Tables 1-3 shows the mean values for the three outputs –students' results on mathematics, readings and science- and for the inputs commented above– being two of them related with the socioeconomic background of the students and the other two inputs refer to the scholar resources. The figures below indicate that the students' results are higher in the *GDPS* in all disciplines and regions, being these differences larger between Basque Country schools. However, the average socioeconomic background, measured by the variables *Pared* and *Hisei*, is normally lower in *PS*. Similarly, *GDPS* present a higher quality of resources, *Schresources*, although the student-teacher ratio (*Stratio*) benefit to *PS*, were the ratio is higher, which implies that each teacher is in charge of a more reduced group of students. This variable captures the labor resources devoted to education.

Table 1: Descriptive statistics of outputs and inputs in Basque Country

	2003				*2006*				*2009*			
Measures	*Mean*	*Std. Dev.*	*Min.*	*Max.*	*Mean*	*Std. Dev.*	*Min.*	*Max.*	*Mean*	*Std. Dev.*	*Min.*	*Max.*
Variables	*Public Schools*											
Math	488.67	30.31	390.79	550.37	477.99	53.47	367.98	574.68	497.61	40.53	389.11	569.44
Read	480.69	30.40	396.83	541.46	464.82	54.95	337.43	584.09	480.02	34.07	405.15	529.89
Science	467.73	32.50	372.59	534.77	474.26	44.51	366.33	562.39	481.58	28.73	414.26	543.18
Pared	11.61	1.22	8.50	13.97	11.86	1.71	8.25	15.68	12.96	1.30	9.82	15.50
Hisei	42.37	6.79	31.13	60.23	44.47	6.78	32.33	62.70	45.55	6.06	32.30	59.53
Schresources	6.21	3.54	1.00	11.00	8.48	2.51	1.00	11.00	9.01	1.55	6.00	11.00
Stratio	14.62	2.45	9.41	20.88	15.54	2.89	11.30	24.30	15.02	2.99	9.15	23.71
Obs.	53				56				68			
Variables	*Government-Dependent Private Schools*											
Math	509.39	34.68	426.83	581.83	512.45	38.62	402.79	584.17	520.73	34.77	436.98	593.48
Read	509.16	37.44	424.02	592.41	500.62	39.03	395.85	590.51	509.52	36.64	411.43	580.1
Science	495.02	36.69	411.3	564.49	505.4	36.91	426.95	597.5	507.56	35.15	391.5	576.13
Pared	12.28	1.21	8.5	14.65	12.89	1.57	9.09	16.17	13.8	1.37	10.41	16.25
Hisei	46.78	8.64	33.62	67.88	49.33	8.42	34.62	68.95	51.53	8.07	35.61	71.57
Schresources	7.89	3.19	1	11	8.06	2.73	1	11	9.08	1.85	4	11
Stratio	6.78	1.18	4.23	10.31	6.89	1.25	4.13	10.37	7.41	1.72	3.96	15.66
Obs.	70				81				90			

Source: Own compilation from PISA 2006

Table 2: Descriptive statistics of outputs and inputs in Castile-Leon

	2003				2006				2009			
Measures	*Mean*	*Std. Dev.*	*Min.*	*Max.*	*Mean*	*Std. Dev.*	*Min.*	*Max.*	*Mean*	*Std. Dev.*	*Min.*	*Max.*
Variables	*Public Schools*											
Math	490.39	30.13	436.37	576.94	511.43	30.53	452.82	577.80	518.06	38.79	425.88	605.77
Read	478.67	29.90	411.87	545.77	472.59	28.51	416.40	513.11	502.00	33.82	412.43	564.46
Science	490.17	33.49	409.61	572.16	519.09	31.49	465.79	588.80	513.71	37.39	403.44	573.45
Pared	11.12	1.13	8.55	13.10	11.33	1.22	9.63	14.65	12.23	1.41	9.25	15.66
Hisei	38.98	5.81	31.46	54.15	41.58	6.20	32.48	56.71	44.33	6.56	32.66	58.85
Schresources	6.69	2.27	1.00	11.00	7.81	2.30	2.00	11.00	8.06	2.37	2.00	11.00
Stratio	10.24	2.23	5.93	15.85	11.23	2.49	6.80	18.75	12.09	2.27	8.08	17.92
Obs.	29				31				31			
Variables	*Government-Dependent Private Schools*											
Math	523.29	34.29	444.33	578.64	526.85	17.07	491.53	557.35	503.76	37.98	446.68	584.82
Read	532.24	37.38	431.85	589.79	499.28	23.59	445.67	534.55	500.24	43.44	417.36	567.36
Science	527.37	37.28	446.99	598.66	530.21	23.80	487.81	570.69	517.32	34.37	465.03	580.05
Pared	12.32	1.25	10.00	14.12	12.46	1.24	10.52	14.97	13.20	1.44	10.25	15.31
Hisei	47.33	7.84	35.00	60.62	47.52	7.34	37.79	63.00	49.88	7.40	37.94	62.09
Schresources	7.07	1.98	2.00	9.00	8.41	2.03	4.00	11.00	7.81	2.29	4.00	11.00
Stratio	5.92	1.20	4.76	9.36	6.43	1.17	4.88	8.94	6.55	1.62	3.68	10.45
Obs.	15				17				14			

Source: Own compilation from PISA 2006

Table 3: Descriptive statistics of outputs and inputs in Catalonia

	2003				2006				2009			
Measures	*Mean*	*Std. Dev.*	*Min.*	*Max.*	*Mean*	*Std. Dev.*	*Min.*	*Max.*	*Mean*	*Std. Dev.*	*Min.*	*Max.*
Variables	*Public Schools*											
Math	476.57	29.03	408.81	526.69	473.17	25.10	409.98	517.02	489.65	40.04	422.37	598.16
Read	461.77	27.10	387.83	502.86	463.54	29.51	388.89	522.32	494.21	32.25	423.62	559.15
Science	486.32	26.29	423.06	529.99	476.99	30.72	416.67	529.40	496.42	39.47	422.94	583.09
Pared	10.71	1.03	8.48	12.27	10.92	1.39	8.02	13.66	11.86	1.68	8.91	15.02
Hisei	43.06	3.63	36.24	51.26	42.76	5.35	34.84	53.10	45.29	5.55	34.20	56.06
Schresources	8.52	2.29	4.00	11.00	8.28	2.23	4.00	11.00	8.98	1.96	5.00	11.00
Stratio	10.22	0.86	8.91	12.85	10.56	1.14	8.32	13.85	10.62	1.11	9.11	13.45
Obs.	25				29				24			
Variables	*Government-Dependent Private Schools*											
Math	503.94	24.71	453.96	544.24	487.33	40.56	384.33	542.17	499.04	41.86	427.60	554.84
Read	498.00	20.78	452.00	530.67	480.82	46.05	376.54	552.65	503.25	43.42	420.45	552.16
Science	512.53	19.06	477.78	550.38	499.10	35.98	428.50	550.77	504.31	37.33	440.43	553.46
Pared	11.66	1.20	9.82	13.55	11.56	1.23	9.75	13.42	12.38	1.83	9.77	15.62
Hisei	48.54	6.97	38.81	60.16	46.45	4.35	40.23	54.13	49.55	9.90	38.94	68.44
Schresources	9.67	1.30	7.00	11.00	8.55	1.86	5.00	11.00	9.42	1.38	8.00	11.00
Stratio	6.50	0.80	5.65	8.13	6.39	0.59	5.43	7.36	6.44	1.52	2.89	8.55
Obs.	12				11				12			

Source: Own compilation from PISA 2006

4. RESULTS

This section presents the main results obtained in our analysis for the Spanish regions Basque Country, Castile-Leon and Catalonia. Our methodology allows us comparing *PS* and *GDPS* productivity changes within 2003-2009.

Tables 4-15 report the results after applying the Educational Malmquist methodology in 2003, 2006 and 2009 considering a set of three outputs and four inputs. Table 4 shows the Educational Malmquist results in 2003, 2006 and 2009 using the Alternative 1 to match the school samples. The first column for each year shows the Educational Malmquist index (*EM*), where *PS* are considered as period *t* and *GDPS* as period *t+1*. After this measure, we report the main Educational Malmquist components: the Efficiency Divergence (*ED*) and the Technological Difference (*TD*). Therefore, Table 5 indicates the 90%, 95% and 99% confidence intervals (*Simar and Wilson* 1999) for the Educational Malmquist indices in each region and their components, being *LB* the Lower Band and *UB* the Upper Band of the interval. This confidence interval allows obtaining the statistical test of the different measures. Tables 6 and 7 refer to the productivity gains between both *PS* and *GDPS* within 2003-2009 using the Alternative 1 and their confidence intervals, respectively. The first column for each year of Table 6 shows the Educational Malmquist Change within two time periods (*EMC*) and its components: the Efficiency Change (*EC*) and the Technological Gap (*TG*), respectively. Tables 8 and 9 replicate the Educational Malmquist for each region using Alternative 2 to match both school type samples and their confidence intervals, respectively. Then, Tables 10 and 11 indicate the regional productivity gains within 2003-2009 using the Alternative 2 and their confidence intervals, respectively. Finally, in order to show the results using the four different alternatives to match units, we propose an empirical analysis for Basque Country. Thus, Tables 12 and 15 report the Educational Malmquist for the Alternatives 1 to 4 (Table 12) and their confidence intervals (Table 13), then the productivity gains between *PS* and *GDPS* within 2003-2009 (Table 14) and their confidence intervals (Table 15).

Tables 4 and 5 show the Educational Malmquist and its components for each period and region, using the Alternative 1 to match the school samples, and the confidence intervals, respectively. The results from Table 4 indicate that public schools are in average significantly more productive than government-dependent private ones each period and for the three Spanish regions. Moreover, two patterns of behavior may be distinguished from Table 4. On the one hand, the productivity of *GDPS* decreases significantly in 2006 with respect to the previous and the following period in Catalonia. On the other hand, the opposite tendency is observed in Basque Country and Castile-Leon, where a significant increase in the productivity of *GDPS* is observed in 2006. Furthermore, differences in productivity are mostly explained by the technological difference among both school ownerships, especially for Basque Country where the technological difference among *PS* and *GDPS* reaches 41% in 2006.

The two following tables show the productivity divergences between both school ownership and the Educational Malmquist components in the three time periods. Nevertheless, with the aim of analyzing the productivity changes within these periods in depth, we calculate the ratios explained in section 2.1. The results after applying the mentioned methodology and the confidence intervals are showed in Tables 6 and 7. As we appreciate in Table 6, the average productivity evolution within 2003-2009 benefits to public schools in Basque Country and Catalonia. This apparently gain for *PS* reflects the reduction in the educational Malmquist index in 2009 related to the same measure in both regions in 2003. On the other hand, the productivity change within 2003-2009 benefits to *GDPS* in Castile-Leon, so a 2% productivity gain is observed within this period, as Table 6 shows. Furthermore, the main component of the Educational Malmquist Change is the technological change for all regions, then apparently *GDPS* present a more advance technology process related to *PS*. Nevertheless, these results are not conclusive, so as we appreciate in Table 7 these results are not significant.

Tables 8 and 9 report the Educational Malmquist index and their confidence intervals for the Malmquist index and their components using Alternative 2, respectively. These results show that *GDPS* are significantly more productive than *PS* each period in all regions. Again, as the results from the Alternative 1, there is a peak in the productivity difference among both school types in 2006 in Basque Country and Castile-Leon, being a productivity difference of 36% (15%) that significantly benefits to *GDPS*. On the other hand, productivity divergences are again explained by the technological gap among both school types and, as Table 9 shows, these results are significant in all regions and each period.

Tables 10 and 11 present the productivity gains among both school types within 2003-2009 and their confidence intervals for the Malmquist index and their components using Alternative 2. Table 10 shows a better and significant productivity evolution for *PS* within 2003-2009 in Basque Country and Castile-Leon, being the productivity change around 1.5% in Basque Country, although the productivity advantage is only significant for *PS* in Basque Country within 2003-2009. On the other hand, *GDPS* are more productive within 2003-2009 in Catalonia, despite this result is not significant, as Table 11 reports. Relating to the better evolution of the public system it must be highlighted that a relative reduction in the productivity gap between *PS* and *GDPS* in 2009 with respect to 2003 period is observed in Basque Country and Castile-Leon. Furthermore, productivity advantage of *GDPS* is mostly explained by the technology gap between both school ownership, being the technological gap higher than 1% in Basque Country and Castile-Leon. However, as it was mentioned in the previous comments for Alternative 1, these results are not significant.

Finally, Tables 12-15 present the results after applying the proposed methodology to Basque Country. Then, Tables 12 and 13 show Educational Malmquist indices in Basque Country for each alternative described in section 2.1. and their confidence intervals, respectively. Several conclusions may remove from Table 12. Firstly, government-dependent private schools are generally more productive than public schools within 2003-2009, independently of the alternative used to match the school samples. Secondly, despite the relevant productivity gap between *PS* and *GDPS*, figures from Table 12 seem to indicate that this *GDPS* advantage is reduced in 2009. Then, the average productivity divergence about 36% in 2006 - it is only higher using Alternative 3 to match school samples- turns significantly to about 22% in 2009. Thirdly, divergences in productivity are significantly explained by the technological component, whose is especially higher in 2006 with a *GDPS* advantage respect to *PS* about 40%. Finally, the simulation for Basque Country seems to indicate that the results are not sensitive to the matching alternative, so both the Educational Malmquist index either the main components have a similar sign independently the alternative used to math both school samples. Thus, we only calculate the Educational Malmquist indices using Alternatives 1 and 2 for Catalonia and Castile-Leon.

Tables 14 and 15 report the productivity gains among both school types in Basque Country using alternatives described in section 2.1. and their confidence intervals, respectively. The main conclusion may remove from Table 14 is that *PS* present a better and significant productive evolution during the period 2003-2009 than *GDPS*. Hence, the Educational Malmquist ratio within this period is always higher than unity, independently the alternative analyzed, indicating the *PS* productivity superiority. Similarly, the general evolution within 2006-2009 again benefits to *PS*. However, it is not the matter in the period 2003-2006, in fact the figures indicate a *GDPS* advantage within this period. With the aim of explaining this apparently opposite results, it must be pointed out that although *GDPS* are more productive each singular year, the disparities between both educational systems reduce in 2009. Thus, it is not strange that the ratio favors *PS* when the period 2009 is considered. Nevertheless, as Table 14 reports, the *GDPS* advantage is not relevant, being always under the 2% independently the alternative used. Finally, the technology gap is significantly the main component in the Educational Malmquist for the ratios 2003-2006 and 2006-2009. However, the analysis of the evolution within 2003-2009 is jointly explained by the efficiency and the technology divergences, but both components are not significant any case. Similarly, the *PS* productivity advantage within the whole period is only significant using the alternative 4.

Table 4: Educational Malmquist Index (Alternative 1)

		2003			2006			2009		
Region	*Statistic*	*EM*	*ED*	*TD*	*EM*	*ED*	*TD*	*EM*	*ED*	*TD*
Basque Country	*Mean*	***1.2405***	0.9934	***1.2522***	***1.3664***	0.9688	***1.4189***	***1.224***	0.9864	***1.2452***
	Std.Dev	0.0195	0.0109	0.0227	0.0254	0.0151	0.027	0.0307	0.0111	0.0362
Castile Leon	*Mean*	***1.1188***	1.0023	***1.1006***	***1.1489***	0.9956	***1.1417***	***1.1335***	1.0268	***1.0886***
	Std.Dev	0.0403	0.0149	0.0234	0.0291	0.0087	0.0111	0.0384	0.0128	0.0197
Catalonia	*Mean*	***1.2077***	0.9963	***1.2018***	***1.1773***	1.0214	***1.143***	***1.2002***	0.9996	***1.1818***
	Std.Dev	0.0288	0.0175	0.0245	0.026	0.0085	0.0141	0.0445	0.0099	0.0138

Source: Own compilation from PISA 2006

Table 5: Confidence interval for Educational Malmquist Index (Alternative 1)

Region	*Basque Country*						*Castile-Leon*						*Catalonia*					
CI	*90%*		*95%*		*99%*		*90%*		*95%*		*99%*		*90%*		*95%*		*99%*	
Measure	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*
	2003																	
EM	***1.2193***	***1.2640***	1.2134	1.2776	1.2045	1.3059	***1.0852***	***1.1946***	1.0804	1.2062	1.0741	1.2352	***1.1800***	***1.2602***	1.1756	1.2721	1.1682	1.2880
ED	0.9796	1.0077	0.9758	1.0116	0.9697	1.0184	0.9831	1.0217	0.9785	1.0271	0.9683	1.0402	0.9736	1.0188	0.9682	1.0249	0.9565	1.0367
TD	***1.2287***	***1.2808***	1.2231	1.2935	1.2135	1.3304	***1.0722***	***1.1321***	1.0630	1.1420	1.0492	1.1594	***1.1710***	***1.2338***	1.1634	1.2433	1.1493	1.2630
	2006																	
EM	***1.3296***	***1.3964***	1.3156	1.4052	1.3004	1.4203	***1.1296***	***1.2116***	1.1280	1.2163	1.1250	1.2259	***1.1548***	***1.2255***	1.1511	1.2363	1.1464	1.2508
ED	0.9492	0.9875	0.9435	0.9934	0.9353	1.0037	0.9849	1.0062	0.9814	1.0090	0.9740	1.0145	1.0110	1.0324	1.0083	1.0363	1.0026	1.0438
TD	***1.3851***	***1.4553***	1.3766	1.4651	1.3605	1.4878	***1.1284***	***1.1556***	1.1253	1.1603	1.1192	1.1736	***1.1263***	***1.1622***	1.1216	1.1675	1.1117	1.1775
	2009																	
EM	***1.1926***	***1.2698***	1.1843	1.2850	1.1708	1.3093	***1.1058***	***1.2114***	1.1036	1.2213	1.1002	1.2414	***1.1732***	***1.2995***	1.1703	1.3051	1.1657	1.3139
ED	0.9719	1.0006	0.9678	1.0044	0.9595	1.0125	1.0100	1.0431	1.0055	1.0472	0.9990	1.0575	0.9873	1.0126	0.9845	1.0173	0.9786	1.0250
TD	***1.2059***	***1.2985***	1.2003	1.3188	1.1878	1.3468	***1.0659***	***1.1177***	1.0599	1.1253	1.0503	1.1378	***1.1638***	***1.1984***	1.1565	1.2030	1.1450	1.2136

Source: Own compilation from PISA 2006

Table 6: Productivity gains between PS and GDPS within 2003-2009 Alternative 1

		Ratio 03-06			Ratio 06-09			Ratio 03-09		
Region	*Statistic*	*EMC*	*EC*	*TG*	*EMC*	*EC*	*TG*	*EMC*	*EC*	*TG*
Basque Country	*Mean*	***0.9081***	1.0256	0.8828	***1.1169***	0.9822	***1.1404***	1.0069	1.0036	1.0031
	Std.Dev	0.0192	0.0193	0.0235	0.0300	0.0187	0.0386	0.0142	0.0078	0.0170
Castile Leon	*Mean*	***0.9737***	1.0068	0.9641	1.0139	0.9697	***1.0491***	0.9935	***0.9880***	1.0055
	Std.Dev	0.0178	0.0174	0.0224	0.0140	0.0151	0.0218	0.0092	0.0095	0.0138
Catalonia	*Mean*	***1.0259***	0.9755	***1.0516***	0.9815	1.0219	***0.9674***	1.0034	0.9984	1.0084
	Std.Dev	0.0159	0.0191	0.0249	0.0191	0.0132	0.0166	0.0101	0.0100	0.0119

Source: Own compilation from PISA 2006

Table 7: Confidence interval for Educational Malmquist Ratios (Alternative 1)

Region	*Basque Country*						*Castile-Leon*						*Catalonia*					
CI	*90%*		*95%*		*99%*		*90%*		*95%*		*99%*		*90%*		*95%*		*99%*	
Measure	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*
	Ratio 2003-2006																	
EMC	***0.8850***	***0.9330***	0.8791	0.9435	0.8674	0.9627	***0.9532***	***0.9985***	0.9488	1.0067	0.9397	1.0229	***1.0061***	***1.0468***	0.9999	1.0527	0.9895	1.0608
EC	1.0009	1.0507	0.9951	1.0583	0.9829	1.0713	0.9847	1.0295	0.9790	1.0369	0.9678	1.0480	0.9506	0.9996	0.9440	1.0067	0.9314	1.0199
TG	***0.8544***	***0.9113***	0.8472	0.9228	0.8323	0.9459	***0.9367***	***0.9935***	0.9279	1.0026	0.9140	1.0202	***1.0196***	***1.0835***	1.0119	1.0934	0.9964	1.1114
	Ratio 2006-2009																	
EMC	***1.0755***	***1.1519***	1.0623	1.1606	1.0376	1.1749	0.9947	1.0302	0.9896	1.0340	0.9760	1.0404	0.9487	1.0025	0.9396	1.0073	0.9312	1.0140
EC	0.9587	1.0058	0.9512	1.0130	0.9405	1.0269	0.9509	0.9889	0.9450	0.9949	0.9361	1.0051	1.0051	1.0382	0.9997	1.0439	0.9890	1.0518
TG	***1.0888***	***1.1872***	1.0716	1.1982	1.0423	1.2156	***1.0188***	***1.0755***	1.0106	1.0825	0.9966	1.0991	***0.9471***	***0.9893***	0.9419	0.9957	0.9319	1.0116
	Ratio 2003-2009																	
EMC	0.9874	1.0231	0.9808	1.0279	0.9703	1.0379	0.9824	1.0053	0.9794	1.0101	0.9737	1.0174	0.9881	1.0152	0.9824	1.0175	0.9766	1.0222
EC	0.9936	1.0135	0.9908	1.0162	0.9862	1.0219	***0.9760***	***0.9999***	0.9724	1.0033	0.9664	1.0123	0.9854	1.0116	0.9819	1.0148	0.9757	1.0216
TG	0.9800	1.0231	0.9727	1.0289	0.9612	1.0426	0.9880	1.0226	0.9827	1.0283	0.9723	1.0369	0.9933	1.0243	0.9893	1.0290	0.9818	1.0358

Source: Own compilation from PISA 2006

Table 8: Educational Malmquist Index (Alternative 2)

		2003			2006			2009		
Region	*Statistic*	*EM*	*ED*	*TD*	*EM*	*ED*	*TD*	*EM*	*ED*	*TD*
Basque	*Mean*	***1.2610***	1.0021	***1.2640***	***1.3630***	0.9842	***1.3922***	***1.2229***	0.9952	***1.2340***
Country	*Std.Dev*	0.0232	0.0101	0.0238	0.0230	0.0132	0.0229	0.0277	0.0103	0.0320
Castile	*Mean*	***1.1262***	0.9865	***1.1310***	***1.1530***	0.9989	***1.1403***	***1.1226***	1.0006	***1.1040***
Leon	*Std.Dev*	0.0290	0.0104	0.0197	0.0325	0.0077	0.0100	0.0438	0.0086	0.0191
Catalonia	*Mean*	***1.1838***	0.9835	***1.1870***	***1.2010***	1.0181	***1.1753***	***1.2006***	0.9829	***1.2030***
	Std.Dev	0.0387	0.0097	0.0147	0.0181	0.0094	0.0196	0.0422	0.0075	0.0111

Source: Own compilation from PISA 2006

Table 9: Confidence interval for Educational Malmquist Index (Alternative 2)

Region	*Basque Country*						*Castile-Leon*						*Catalonia*					
CI	*90%*		*95%*		*99%*		*90%*		*95%*		*99%*		*90%*		*95%*		*99%*	
Measure	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*
	2003																	
EM	***1.235***	***1.2887***	1.2239	1.303	1.2096	1.3308	***1.1007***	***1.1767***	1.0978	1.1857	1.0925	1.2104	***1.1568***	***1.2645***	1.1539	1.2739	1.1492	1.291
ED	0.9888	1.0151	0.9861	1.0191	0.9805	1.0264	0.9732	0.9999	0.9694	1.0033	0.9625	1.0097	0.971	0.9959	0.9679	0.9994	0.9617	1.0063
TD	1.2387	1.2944	1.2341	1.3097	1.2233	1.3402	***1.1083***	***1.1584***	1.1029	1.1684	1.0926	1.1871	***1.1707***	***1.208***	1.1658	1.2149	1.1582	1.2265
	2006																	
EM	***1.3279***	***1.3898***	1.3149	1.3948	1.3023	1.4069	***1.1312***	***1.2215***	1.1293	1.2273	1.1255	1.2399	***1.1812***	***1.2265***	1.1789	1.2327	1.1751	1.256
ED	0.9668	1.0009	0.9624	1.0067	0.9554	1.0142	0.9887	1.0086	0.9856	1.0105	0.9786	1.0137	1.0062	1.0296	1.0019	1.032	0.992	1.0363
TD	***1.363***	***1.4219***	1.3561	1.4317	1.3448	1.4482	***1.1288***	***1.1529***	1.1265	1.1585	1.1225	1.17	***1.1552***	***1.2029***	1.1529	1.2129	1.1474	1.2388
	2009																	
EM	***1.1936***	***1.2618***	1.1823	1.2754	1.1718	1.3064	***1.0906***	***1.2105***	1.0882	1.222	1.0846	1.2453	***1.1758***	***1.2944***	1.1741	1.2993	1.1707	1.3083
ED	0.9821	1.0086	0.9783	1.0124	0.9709	1.0189	0.9891	1.0114	0.9861	1.014	0.9794	1.0198	0.9732	0.992	0.9703	0.9943	0.9637	0.9999
TD	***1.199***	***1.2794***	1.1941	1.2951	1.1818	1.3258	***1.0831***	***1.1328***	1.0796	1.1393	1.0737	1.1516	***1.1901***	***1.2174***	1.1864	1.2228	1.18	1.2312

Source: Own compilation from PISA 2006

Table 10: Productivity gains between PS and GDPS within 2003-2009 (Alternative 2)

		Ratio 03-06			*Ratio 06-09*			*Ratio 03-09*		
Region	*Statistic*	*EMC*	*EC*	*TG*	*EMC*	*EC*	*TG*	*EMC*	*EC*	*TG*
Basque Country	*Mean*	***0.9255***	1.0183	***0.9080***	***1.1150***	0.9890	***1.1293***	***1.0156***	1.0034	1.0124
	Std.Dev	0.0177	0.0172	0.0221	0.0267	0.0168	0.0347	0.0133	0.0071	0.0162
Castile Leon	*Mean*	***0.9773***	0.9877	0.9917	***1.0270***	0.9983	***1.0333***	1.0019	0.9930	1.0122
	Std.Dev	0.0151	0.0129	0.0191	0.0172	0.0116	0.0196	0.0114	0.0067	0.0123
Catalonia	*Mean*	0.9853	0.9661	1.0105	1.0015	1.0359	0.9770	0.9930	1.0003	0.9935
	Std.Dev	0.0265	0.0129	0.0206	0.0279	0.0125	0.0184	0.0052	0.0062	0.0077

Source: Own compilation from PISA 2006

Table 11: Confidence interval for Educational Malmquist Ratios (Alternative 2)

Region	*Basque Country*						*Castile-Leon*						*Catalonia*					
CI	*90%*		*95%*		*99%*		*90%*		*95%*		*99%*		*90%*		*95%*		*99%*	
Measure	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*	*LB*	*UB*
	Ratio 2003-2006																	
EMC	***0.9046***	***0.9481***	0.8999	0.9568	0.8903	0.9776	***0.9595***	***0.9972***	0.9546	1.0062	0.9463	1.0177	0.9570	1.0324	0.9507	1.0422	0.9421	1.0605
EC	0.9959	1.0407	0.9905	1.0469	0.9815	1.0572	0.9707	1.0043	0.9674	1.0092	0.9589	1.0191	0.9503	0.9829	0.9458	0.9877	0.9362	0.9976
TG	***0.8814***	***0.9355***	0.8739	0.9464	0.8617	0.9680	0.9689	1.0179	0.9635	1.0258	0.9508	1.0419	0.9834	1.0351	0.9736	1.0431	0.9586	1.0559
	Ratio 2006-2009																	
EMC	***1.0780***	***1.1454***	1.0652	1.1538	1.0410	1.1643	***1.0040***	***1.0466***	0.9965	1.0513	0.9824	1.0610	0.9469	1.0306	0.9377	1.0369	0.9302	1.0464
EC	0.9680	1.0104	0.9618	1.0171	0.9505	1.0304	0.9836	1.0136	0.9792	1.0179	0.9712	1.0241	1.0200	1.0515	1.0152	1.0558	1.0047	1.0636
TG	***1.0823***	***1.1709***	1.0670	1.1819	1.0408	1.2004	***1.0054***	***1.0576***	0.9988	1.0627	0.9879	1.0750	0.9558	1.0026	0.9514	1.0116	0.9439	1.0319
	Ratio 2003-2009																	
EMC	0.9981	1.0309	0.9928	1.0363	0.9804	1.0484	0.9863	1.0153	0.9812	1.0194	0.9735	1.0272	***0.9865***	***0.9996***	0.9849	1.0021	0.9818	1.0071
EC	0.9944	1.0127	0.9918	1.0153	0.9874	1.0202	0.9843	1.0016	0.9821	1.0038	0.9780	1.0087	0.9924	1.0082	0.9899	1.0104	0.9860	1.0151
TG	0.9908	1.0315	0.9847	1.0371	0.9732	1.0504	0.9960	1.0274	0.9918	1.0318	0.9828	1.0418	0.9840	1.0039	0.9812	1.0067	0.9764	1.0132

Source: Own compilation from PISA 2006

Table 12: Educational Malmquist Index in Basque Country

		2003			2006			2009		
Alternative	*Statistic*	*EM*	*ED*	*TD*	*EM*	*ED*	*TD*	*EM*	*ED*	*TD*
A1	*Mean*	***1.2405***	0.9934	***1.2522***	***1.3664***	0.9688	***1.4189***	***1.2240***	0.9864	***1.2452***
	Std.Dev	0.0195	0.0109	0.0227	0.0254	0.0151	0.0270	0.0307	0.0111	0.0362
A2	*Mean*	***1.2610***	1.0021	***1.2638***	***1.3627***	0.9842	***1.3922***	***1.2229***	0.9952	***1.2336***
	Std.Dev	0.0232	0.0101	0.0238	0.0230	0.0132	0.0229	0.0277	0.0103	0.0320
A3	*Mean*	***1.2516***	0.9947	***1.2620***	***1.3703***	0.9732	***1.4176***	***1.2253***	0.9887	***1.2441***
	Std.Dev	0.0201	0.0110	0.0231	0.0266	0.0145	0.0267	0.0303	0.0109	0.0347
A4	*Mean*	***1.2379***	0.9961	***1.2452***	***1.3631***	0.9809	***1.3999***	***1.2068***	0.9940	***1.2185***
	Std.Dev	0.0121	0.0091	0.0141	0.0263	0.0131	0.0219	0.0179	0.0099	0.0207

Source: Own compilation from PISA 2006

Table 13: Confidence interval for Educational Malmquist in Basque Country

		2003			2006			2009		
Alternative	*Statistic*	*EM*	*ED*	*TD*	*EM*	*ED*	*TD*	*EM*	*ED*	*TD*
A1	*Mean*	***1.2405***	0.9934	***1.2522***	***1.3664***	0.9688	***1.4189***	***1.2240***	0.9864	***1.2452***
	Std.Dev	0.0195	0.0109	0.0227	0.0254	0.0151	0.0270	0.0307	0.0111	0.0362
A2	*Mean*	***1.2610***	1.0021	***1.2638***	***1.3627***	0.9842	***1.3922***	***1.2229***	0.9952	***1.2336***
	Std.Dev	0.0232	0.0101	0.0238	0.0230	0.0132	0.0229	0.0277	0.0103	0.0320
A3	*Mean*	***1.2516***	0.9947	***1.2620***	***1.3703***	0.9732	***1.4176***	***1.2253***	0.9887	***1.2441***
	Std.Dev	0.0201	0.0110	0.0231	0.0266	0.0145	0.0267	0.0303	0.0109	0.0347
A4	*Mean*	***1.2379***	0.9961	***1.2452***	***1.3631***	0.9809	***1.3999***	***1.2068***	0.9940	***1.2185***
	Std.Dev	0.0121	0.0091	0.0141	0.0263	0.0131	0.0219	0.0179	0.0099	0.0207

Source: Own compilation from PISA 2006

Table 14: Productivity gains between PS and GDPS within 2003-2009 in Basque Country

		Ratio 03-06			Ratio 06-09			Ratio 03-09		
Alternative	Statistic	EMC	EC	TG	EMC	EC	TG	EMC	EC	TG
A1	Mean	**0.9081**	1.0256	**0.8828**	**1.1169**	0.9822	**1.1404**	1.0069	1.0036	1.0031
	Std.Dev	0.0192	0.0193	0.0235	0.0300	0.0187	0.0386	0.0142	0.0078	0.0170
A2	Mean	**0.9255**	1.0183	**0.9080**	**1.1148**	0.9890	**1.1293**	1.0156	1.0034	1.0124
	Std.Dev	0.0177	0.0172	0.0221	0.0267	0.0168	0.0347	0.0133	0.0071	0.0162
A3	Mean	**0.9136**	1.0223	**0.8905**	**1.1188**	0.9844	**1.1404**	1.0108	1.0030	1.0074
	Std.Dev	0.0197	0.0188	0.0230	0.0300	0.0184	0.0382	0.0139	0.0077	0.0164
A4	Mean	**0.9084**	1.0157	**0.8897**	**1.1296**	0.9869	**1.1492**	**1.0129**	1.0011	1.0110
	Std.Dev	0.0166	0.0164	0.0173	0.0203	0.0162	0.0261	0.0080	0.0068	0.0104

Source: Own compilation from PISA 2006

Table 15: Confidence interval for Educational Malmquist Ratios in Basque Country

Alternative	Alternative 1						Alternative 2						Alternative 3						Alternative 4					
CI	90%		95%		99%		90%		95%		99%		90%		95%		99%		90%		95%		99%	
Measure	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB
	Ratio 2003-2006																							
EMC	**0.8850**	**0.9330**	0.8791	0.9435	0.8674	0.9627	**0.9046**	**0.9481**	0.8999	0.9568	0.8903	0.9776	**0.8909**	**0.9392**	0.8836	0.9479	0.8702	0.9680	**0.8891**	**0.9327**	0.8851	0.9404	0.8774	0.9537
EC	1.0009	1.0507	0.9951	1.0583	0.9829	1.0713	0.9959	1.0407	0.9905	1.0469	0.9815	1.0572	0.9987	1.0460	0.9916	1.0532	0.9803	1.0676	0.9943	1.0369	0.9889	1.0432	0.9798	1.0547
TG	**0.8544**	**0.9113**	0.8472	0.9228	0.8323	0.9459	**0.8814**	**0.9355**	0.8739	0.9464	0.8617	0.9680	**0.8627**	**0.9195**	0.8560	0.9290	0.8392	0.9517	**0.8678**	**0.9123**	0.8621	0.9179	0.8503	0.9312
	Ratio 2006-2009																							
EMC	**1.0755**	**1.1519**	1.0623	1.1606	1.0376	1.1749	**1.0780**	**1.1454**	1.0652	1.1538	1.0410	1.1643	**1.0770**	**1.1545**	1.0636	1.1616	1.0388	1.1744	**1.1024**	**1.1539**	1.0932	1.1603	1.0751	1.1711
EC	0.9587	1.0058	0.9512	1.0130	0.9405	1.0269	0.9680	1.0104	0.9618	1.0171	0.9505	1.0304	0.9610	1.0080	0.9545	1.0143	0.9411	1.0289	0.9658	1.0080	0.9604	1.0147	0.9511	1.0249
TCG	**1.0888**	**1.1872**	1.0716	1.1982	1.0423	1.2156	**1.0823**	**1.1709**	1.0670	1.1819	1.0408	1.2004	**1.0890**	**1.1860**	1.0719	1.1974	1.0409	1.2201	**1.1153**	**1.1807**	1.1038	1.1893	1.0775	1.2056
	Ratio 2003-2009																							
EMC	0.9874	1.0231	0.9808	1.0279	0.9703	1.0379	0.9981	1.0309	0.9928	1.0363	0.9804	1.0484	0.9922	1.0268	0.9853	1.0312	0.9745	1.0416	**1.0026**	**1.0221**	0.9986	1.0247	0.9900	1.0304
EC	0.9936	1.0135	0.9908	1.0162	0.9862	1.0219	0.9944	1.0127	0.9918	1.0153	0.9874	1.0202	0.9931	1.0129	0.9903	1.0159	0.9856	1.0209	0.9923	1.0097	0.9898	1.0122	0.9862	1.0174
TG	0.9800	1.0231	0.9727	1.0289	0.9612	1.0426	0.9908	1.0315	0.9847	1.0371	0.9732	1.0504	0.9848	1.0271	0.9777	1.0321	0.9649	1.0427	0.9973	1.0231	0.9925	1.0265	0.9824	1.0334

Source: Own compilation from PISA 2006

5. CONCLUSIONS

Malmquist Index methodology is widely use in the literature with the aim of measuring the productivity growth within two time periods as the distance between each *DMU* and the frontier for each period. However, the traditional Malmquist index needs a panel database to be implemented, so it focuses on analyzing the evolution of the same unit along the time.

In this paper, we propose a new approach that allows us to deepen on the productivity divergences between different units within the same year. Thus, an Educational Malmquist is built for comparing the average productivity discrepancies between publicly finance educational system, which includes both public and government-dependent private schools, when only a pseudo-panel database is available.

With this aim, we use school data from PISA 2003, 2006 and 2009 that provide us with wide information about the educational context in three Spanish regions: Basque Country, Castile-Leon and Catalonia. Nevertheless, this alternative is only available for comparing average differences between publicly finance schools, so students and schools are different each wave. On the other hand, different approaches to pairing school samples are developed, including balance and unbalanced sub-samples, with the aim of showing that Educational Malmquist results are not sensitive to the matching alternative. Finally *Simar and Wilson* (1999) approach is used to obtain confidence intervals for the Malmquist indices and their components through the bootstrap methodology.

The main results remove for our analysis may be summarizing as follows. Firstly, government-dependent private schools are generally more productive than public ones each individual period. Thus, independently of the alternative used to match different school type's samples, in average government-dependent private school generally outperform public ones, due to the technological superiority for *GDPS.* However, the average productivity evolution within 2003-2009 generally benefits to public schools, as a consequence of the relative reduction in the productivity discrepancies between both school ownerships in the period 2009 related to the previous years. More in depth, although public schools are more productive year by year, the differences are shortening within 2003-2009.

Hence, several conclusions may highlight from the empirical analysis for these three Spanish regions- Basque Country, Castile-Leon and Catalonia. Firstly, the process to match different school types samples is not relevant due to the productivity evolution is quite similar in Basque Country after using different alternatives to pairing the school samples each year.

Secondly, considering the proportion of teacher in charge of a group of students, it benefits to government-dependent private schools. This result may be a consequence of the relative advantage in public school, so these last schools present a higher proportion of teacher related to the total number of registered students. Hence, Educational Malmquist is built using DEA methodology to obtain the distance of each unit to the frontiers, so public schools are penalized due to the present a better input endowment comparing with government-dependent private ones. Thirdly, a reversed v shape pattern is observed in the productivity evolution in all regions. Thus, the productivity gain for government-dependent private schools increases in 2006, which is considerably higher than in the previous and the following years. In fact a widely analysis about the public educational system characteristic during this period is necessary to explain this pattern of behavior. Finally, our results seem to indicate that more similar average family characteristics among schools will increase the productivity in the public educational system. Nevertheless, these conclusions should be interpreted cautiously, since they are referred to a particular context and time however their implications are very relevant for the design of educational-policy.

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CONCLUSIONES

This doctoral thesis has focused on the efficiency analysis of secondary education in Spain from both a temporal and a regional perspective. To this end, different waves of the PISA database and alternative methodological approaches and units of analysis have been used.

Since each chapter closed with a summary of their main results, this section will provide some general conclusions which will be related to different educational policy measures. Possible lines of future research will then be identified.

Because of its effects on academic achievement, it stands out the importance of the student's socioeconomic characteristics among the individual factors. The peer effect, one of the school factors, is not quite so strong, but is still very relevant for the results. Unlike the previous two factors, traditional school resources have little effect in explaining academic achievement, and their effects may be even zero (as is the case for the student-teacher ratio). These results are in line with those obtained using other techniques (multilevel, mainly) for other countries (*Hanushek* 2003) as well as for Spain (*Calero and Escardíbul* 2007, *Calero et al.* 2009). With regard to the effect of a series of control variables, the immigrant status (whether first or second generation) and repeating a year are negatively associated with the students' efficiency. From a regional perspective, the group of regions with a representative sample is, with the exception of Andalusia and Catalonia, more efficient than the rest, being Castile-Leon and La Rioja the most efficient Regions within the former group. Finally, when decomposing the inefficiency unexplained by the control variables it is found that a major part (87%) corresponds to the students, with only 13% being associated with the schools.

The results of the efficiency analysis allow one to discuss different educational policy proposals, including some that came to the forefront of the political debate in the last regional elections[73].

The effects on academic results do not support the proposed solution of increasing the school resources. Neither does reducing the number of students per class

73 It was the case of Madrid, with proposals of reducing the number of pupils per class (PSOE) or segregating the pupils (PP).

seem to improve their efficiency, apart from the difficulty of increasing the number of teachers and the additional costs that this would involve.

Regarding policies of educational segregation, the importance of the peer effects should be taken into account. Although segregating the best students could increase their academic results, reducing educational segregation would likely lead not only to a reduced inequality in academic achievement but also to a rise in its aggregate level.

The negative effect on efficiency of repeating a year sounds a warning about the complexity and magnitude of the problem. This is a widespread phenomenon in our country[74] and is a clear sign of general school failure, which also reaches very high relative levels in Spain[75]. It seems advisable to act at early ages and in several directions in coherence with the complexity of the problem, going beyond the purported solution of just repeating the year.

The inefficiency part explained by the schools is small, what can be seen as an element of equity in the educational system, positive therefore in the sense that, once personal characteristics are taken into account, it indicates an absence of major differences in results due to the fact of attending one or another school. Moreover, the importance of the inefficiency explained by the students and the relevance of their socioeconomic level in the academic results point to the need for wide-ranging policies in order to reduce socioeconomic inequalities. The irrelevance of the school ownership (whether public or government-dependent private school) disappears when quasi-experimental techniques are applied to avoid any bias in the students' selection. In this case, the government-dependent private schools appear to be more efficient, although the spatial analysis show the results to vary from one Region to another, thus indicating that it would be an error to draw any general conclusions in this regard.

Finally, regarding future lines of research, two areas may be considered. One is straightforward and would replicate the regional analysis of educational efficiency by

74 According to PISA 2009, repetition of a year affects a third of the pupils in Spain, at some 23 points above the OCDE mean and 21.5 points above the EU mean (OECD, 2010).

75 Understood as the early drop-out of education or the percentage of the 18-24 year old population who have not completed the second stage of Secondary Education and who are not following any kind of formal studies or professional training. The figure for Spain in 2010 was 28.4%, twice the average of the EU (Ministerio de Educación, 2011).

school ownership using the data provided by the 2009 wave of PISA. The other would extend the application of the Educational Malmquist Index to more Regions on the basis of the samples of 2006 and 2009. Furthermore, there would be methodological interest, for example, in estimating the Educational Malmquist Index by means of parametric techniques that would allow a sensitivity analysis of the results to be made, or in applying a Monte Carlo approach to estimate the confidence intervals of that index instead of the bootstrap technique proposed by *Simar and Wilson* (1999) and which has been used in the present work.

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