Comparing school ownership performance using a pseudo-panel database: a Malmquist-type index approach

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Abstract

The Malmquist Index methodology is widely used in production economics for measuring the productivity changes of a set of decision making units (DMUs) within different time periods. Moreover, it is quite usual in the management literature to compare public and private DMU performance operating under the same economic sector. However, the standard Malmquist index needs a panel database to be implemented, i.e. it focuses on analyzing the evolution of the same DMUs over time. In this paper, we propose a different way of using the Malmquist index that allows us to further analyze the performance divergences between public and private DMUs when only a pseudo-panel database is available. The paper extends Camanho and Dyson's one-period Malmquist-type index (Camanho and Dyson, 2006) using a pseudo-panel database. We apply this methodology to examine the plausible differences in public and private government-dependent high schools productivity for three Spanish Regions -Catalonia, Castile-Leon and Basque Country- which entered representative samples in PISA 2003, 2006 and 2009. Finally, in order to achieve a measure of the significance of results, we use the bootstrap methodology proposed by Simar and Wilson (1999) to obtain the confidence intervals for the Malmquist-type indices and their components. The results suggest a persistent and significant higher performance of private government-dependent schools over public ones in all three Spanish regions. Moreover, this difference persists over time.

Keywords: Efficiency, Productivity, Education, Pseudo-panel, Malmquist Index.

1. INTRODUCTION

Traditionally, the Malmquist index, proposed by *Caves et al.* (1982), is used to measure productivity changes between two or more periods, implying that the same group of units is observed in all considered periods. However, in some economic fields, like education or health, it is common to extract random waves of representative samples of DMUs (hospitals, primary health care units, primary and high schools, etc.) in order to analyze their resources, activities, results and performance. The DMUs contained in each wave vary from one year to another, being mostly anonymous for researchers, so we will call this information a pseudo-panel database.

Inefficiency in education may arise, affecting school performance, due to multiple factors; such as the lack of motivation from students and teachers, pedagogical issues, class organization, school management or the quality and experience of teachers. Thus, Levin (1974) provides six different causes[1] to expect inefficient behaviors in schools. There is a wide literature focus on the school type performance, so private schools usually achieve better average results than students who attend public schools. Then, some studies directly compare public and private high school management from an economic perspective, however most of the previous educational literature attribute this private schools advantage because market competition should force them to achieve a more efficient use of resources and provide high standards of quality to their students (Alchian 1950; Friedman and Friedman 1981; Chubb and Moe 1990; Hoxby 2003). Nevertheless, copious research has not provided solid evidence about the superiority of either school type. Some studies claim an advantage for private schools (Witte 1992; Angrist *et al.* 2002; Krueger and Zhu 2004; Vandenberghe and Robin 2004; Duncan and Sandy 2007; Crespo-Cebada *et al.* 2014), whereas others do not find statistical differences according to school ownership (Goldhaber 1996; McEwan 2001; Perelman and Santín, 2011), or even conclude that public education is significantly better than private schooling (Kirjavainen and Loikkanen 1998; Newhouse and Beegle 2006; Mancebón *et al.* 2012).

In order to tackle the inefficiency measurement issue in education at school level many studies have used the non-parametric data envelopment analysis (Muñiz, 2002 and Mancebón *et al.* 2012)[2]. However, only a few have applied the Malmquist index to examine productivity changes in schools (three exceptions are Maragos and Despotis (2004), Brennan *et al.* (2013)

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[1] These six items are; lack of knowledge about the production set, lack of management autonomy to allocate inputs, little or no competition among schools, input and output prices not available to educational managers, weak incentive structure inside the schools and lack of yardstick competition studies. For a detailed discussion see Levin (1974, 157-161).

[2] For a review, see Worthington (2001).

and Essid *et al.* (2013)). A possible explanation for this lack of empirical studies applying the Malmquist index for benchmarking schools may be due to the difficulty to obtain administrative panel databases from educational authorities.

However, the recent increase of national and international programs to evaluate educational achievement over the last decades reveals a higher policy concern about educational performance (Hanushek and Kimko, 2000; Hanushek and Woessman, 2008; De la Fuente, 2011). Hence, along last few years, some international projects have been intensively developed in order to evaluate educational achievement for the vehicular disciplines: Science, Mathematics and Reading. 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 international programs is that provide an external evaluation of the academic trying to identify the causes of school failure, allowing policy makers and school principals to explore their management strengths and weaknesses in depth. Nevertheless, the comparison of student or the school behaviors over time is not straightforward using these international studies so participant schools and students differ from one wave to another.

This study attempts to analyze the main divergences in the publicly funded educational system in Spain. The analysis incorporates information about the different background depending on school ownership[3], taking into account the school resources differences and also the students' family and personal characteristics discrepancies from one school type to another. Then, a new approach is proposed to compare the performance of different sample groups of representative DMUs using the Malmquist index when only a pseudo-panel database is available. This method extends Camanho and Dyson's Malmquist-type index (Camanho & Dyson, 2006) (CDMI from now on) for measuring and comparing the productivity of two groups of DMUs in one period[4].

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[3] To analyze potential schools and students non-observed differences in the publicly financed school system in Spain, see Crespo-Cebada *et al*. (2014).

[4] A similar strategy was developed by Berg *et al.* (1993) with the aim of comparing banking efficiencies in three Nordic countries or Balk and Althin (1996) to compare the evolution of Swedish pharmacy productivity over the 1980-1989 period. Both papers propose new strategies to calculate the Malmquist index, taking a particular unit as the comparison reference or taking a fixed period as the baseline in order to calculate multi-period Malmquist indices, respectively, and both alternatives satisfy the transitivity property.

With the aim of showing our proposal's potential we include an empirical application in the educational framework in order to test possible productivity disparities among public schools (*PS*) and private government dependent schools (*PGDS*) over three time periods (2003, 2006 and 2009) on the publicly funded educational system in Spain. Hence, three Spanish regions- Castile-Leon, Catalonia and Basque Country- are analyzed. These regions participated with an extended representative sample in the *Programme for International Student Assessment* (PISA), administered in 2003, 2006 and 2009 by the Organization for Economic Cooperation and Development (OECD).

The paper is organized as follows. Section 2 provides an overview of the Malmquist index, the CDMI and our estimation strategy for a pseudo-panel. Moreover, we propose two different alternatives to match both school type samples for each considered period. Finally, we introduce the Simar and Wilson's (1999) approach to calculate the confidence intervals for the productivity indices and their components. The educational data set and the selected inputs and outputs are described in section 3. Section 4 reports the results after applying our strategy and a discussion of our empirical analysis. Finally, the last section shows the main conclusionsof our study.

2. METHODOLOGY

2.1. The Malmquist index

The 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. The index may be 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 outputs are involved in the learning process; prices are unknown or difficult to estimate, and the technology that relates the input and the output vector is completely unknown.

To formalize the index we assume constant returns to scale (CRS)[5], so we implicitly assume that school sizes and resources are quite similar for each region over time. Defining a vector of inputs $x = (x_1, ..., x_K) \in \Re^{K+}$ and a vector of outputs $y = (y_1, ..., y_S) \in \Re^{S+}$; then a feasible multi-

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[5] There are other studies that also consider variable returns to scale such as Balk and Althin (1996), Ray and Desli, (1997) and Forsund (2002). A future research line would be to further decompose the Malmquist-type index presented in this work to take into account this kind of returns to scale. In the case of empirical applications in education, variables are usually normalized to avoid school size issues.

input and multi-output production technology for a period of time t $(t = 1....,T)$ may be defined using the output possibility set $P^t(x^t)$. This output possibility set can be produced using the input vector x^t as $P^t(x^t) = \{y^t\text{: } x^t \text{ can produce } y^t\}$, 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):

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

where $D^t\left(x^t, y^t\right)$ is the inverse of the factor by which the production of all output quantities could be increased in order to belong to the frontier if the inputs are kept constant. From Equation (1), 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 , the DMU is located behind the outer boundary of the output possibility set and is considered inefficient. Then an output-oriented Malmquist productivity index based on period t technology can be defined as:

$$M^t\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)}. \tag{2}$$

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 two periods of time t and $t+1$. The analytical expression of the index would be:

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

where an index higher (lower) than one implies productivity improvements (losses)[6]. Furthermore, Equation (3) may be decomposed into two components. The first item reflects the technical efficiency change (TEC), which captures the efficiency improvements (reductions) in period $t+1$ if $TEC > 1$ ($TEC < 1$), whereas $TEC = 1$ indicates no changes in technical efficiency. The second measure represents the technological change (TC) in period $t+1$ with respect to period t, whose sign may be analyzed in a similar way to TEC, although both measures may have different directions.

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[6] This productivity index is the geometric mean of two productivity indices, where the baseline is period t for the first period and $t+1$ for the second one, avoiding an arbitrary selection of the reference period.

2. 2. The Camanho- Dyson Malmquist Index (CDMI) approach

The Malmquist index methodology requires observing a group of DMUs in different periods, for which purpose a panel database needs to be implemented. However, this approach is unable to explore the potential disparities among different groups of units whose organizational structure and background circumstances vary over time. To overcome this problem Camanho and Dyson (2006) proposed a Malmquist-type index in order to achieve an average indicator of the relative performance of two or more groups within a period when the organizational and managerial guidelines differ as happens with the school ownership case.

The CDMI is an adaptation of the Malmquist index to provide a cross-sectional comparison of the performance of DMUs operating under different conditions rather than a measurement of the productivity change between two periods. They defined an overall measure for comparing the performance between two (or more) groups of DMUs, in our case different school ownerships, by replacing the super-indices t and t+1 related to the period by G (government-dependent private schools) and P (public schools). Consider *N* DMUs ($j = 1 \ldots N$) in group *G*, using an input vector $x^G \in \Re^{K+}$ to produce outputs $y^G \in \Re^{S+}$, where the input-output vector for DMU$_j$ in group G is denoted by (x_j^G, y_j^G), and $D^G(x_j^G, y_j^G)$ represents the output distance function for DMU "*j"* with respect to the frontier of group *G*. Similarly, consider *M* DMUs $i = 1 \ldots M$, in group *P* using an input vector $x^P \in \Re^{K+}$ to produce outputs $y^P \in \Re^{S+}$, where the input-output vector for DMU$_i$ in group *P* is denoted by (x_i^P, y_i^P), and $D^P(x_i^P, y_i^P)$ represents the output distance function for DMU "*i*" with respect to the frontier of group P. The CDMI for comparing the performance of two groups of DMUs associated with different programs, ownerships or educational practices can be defined as follows in Equation (4):

$$\mathrm{CDMI}^{\mathrm{GP}} = \left[\frac{\left(\prod_{j=1}^{N} D^G(x_j^G, y_j^G) \right)^{1/N}}{\left(\prod_{i=1}^{M} D^G(x_i^P, y_i^P) \right)^{1/M}} \cdot \frac{\left(\prod_{j=1}^{N} D^P(x_j^G, y_j^G) \right)^{1/N}}{\left(\prod_{i=1}^{M} D^P(x_i^P, y_i^P) \right)^{1/M}} \right]^{1/2} \tag{4}$$

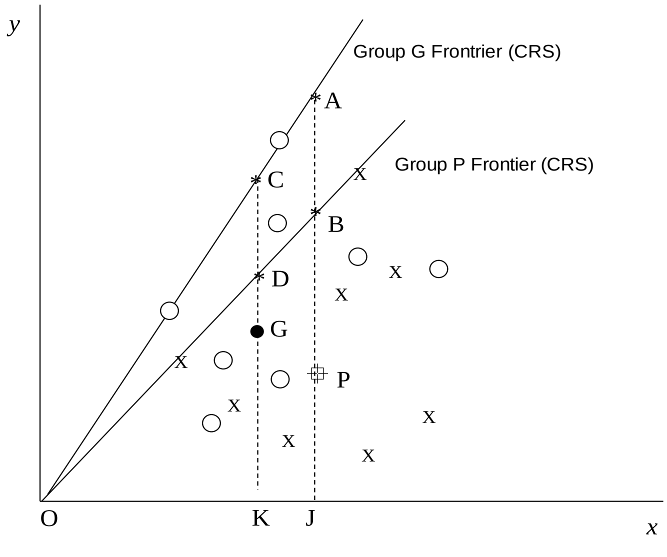
The two ratios inside square brackets evaluate the average distance of the two groups of DMUs with respect to a single reference technology. The first (second) ratio measures the relative average performance of both groups using group *G* (*P*) technology. As the standard Malmquist index, we have no reason to prefer either, the frontier of *G*s or *P*s, so the CDMI takes the geometric mean of both. Using this index it is possible to compare the performance of both groups using all available information. The CDMI is straightforward to interpret: a value higher than one indicates better average performance for group *G* than for group *P*. This within-groups comparison measure can be decomposed by rewriting Equation 4 as follows:

$$\mathrm{CDMI}^{\mathrm{GP}} = \frac{\left(\prod_{j=1}^{N} D^{G}(x_j^G, y_j^G)\right)^{1/N}}{\left(\prod_{i=1}^{M} D^{P}(x_i^P, y_i^P)\right)^{1/M}} \cdot \left[\frac{\left(\prod_{j=1}^{N} D^{P}(x_j^G, y_j^G)\right)^{1/N}}{\left(\prod_{j=1}^{N} D^{G}(x_j^G, y_j^G)\right)^{1/N}} \cdot \frac{\left(\prod_{j=1}^{M} D^{P}(x_i^P, y_i^P)\right)^{1/M}}{\left(\prod_{i=1}^{M} D^{G}(x_i^P, y_i^P)\right)^{1/M}} \right]^{1/2} \qquad (5)$$

Equation (5) again shows the average productivity differences between both G-P groups in one year. The ratio outside square brackets compares within-group average efficiencies measuring the efficiency gap between both groups, EG^{GP} and the ratio inside square brackets shows the productivity or technological gap between the frontiers of the two groups, TG^{GP}.

Figure 1 illustrates these concepts in order to compare two groups of DMUs in one period. Let us assume that the *G* Frontier (CRS) and *P* Frontier (CRS) represent the constant returns to scale technologies for both *PGDS* and *PS*, respectively.

Figure 1: Productivity divergences between PS and GDPS



where circles represent the *N* DMUs in group *G;* whereas crosses represent the *M* DMUs in group *P*. This production activity information is used to estimate both production frontiers using DEA. Consequently, we estimate the distance of each school to its own frontier. Then, the geometric average efficiency of each group with respect to its own frontier and the comparison group frontier is estimated. In Figure 1, dots *G* and *P* denote this theoretical average production activity for both groups, only considering the performance of DMUs belonging to the same group. Therefore, according to Equation (5), we obtain the required distances to estimate the CDMI as follows:

$$\frac{KG}{KC}=\left(\prod_{j=1}^{N} D^{G}(x_j^G, y_j^G)\right)^{1/N}, \tag{6}$$

$$\frac{JP}{JB}=\left(\prod_{i=1}^{M} D^{P}(x_i^P, y_i^P)\right)^{1/M}, \tag{7}$$

$$\frac{KG}{KD}=\left(\prod_{j=1}^{N} D^{P}(x_j^G, y_j^G)\right)^{1/N}, \tag{8}$$

$$\frac{JP}{JA}=\left(\prod_{i=1}^{M} D^{G}(x_i^P, y_i^P)\right)^{1/M} \tag{9}$$

The CDMI approach is able to evaluate only the average discrepancies among both school groups but it is not suitable for specific school behaviors[7]. One advantage of this approach over Charnes *et al.* well-known methodology (Charnes *et al.*, 1981) is that the CDMI does not need to pool the DMUs together to build a common frontier[8].

2.3. The CDMI extended for a pseudo-panel database

The CDMI provides an opportunity to monitor the educational system despite the lack of panel databases in education. As mentioned before, the number of national and international pseudo-panel databases of schools available for research has grown last years. A pseudo-panel database consists of different waves of representative school samples, where participant schools and students vary from one wave to another.

With the aim of analyzing the evolution of the school ownership divergences[9] within two time periods, we propose to build the ratio of two CDMIs calculated for two periods. This strategy allows us to check which organizational pattern behaves better over time in order to infer

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[7] Camanho and Dyson (2006) show their index can also be used to compare more than two groups for a more general setting. The CDMI for more than two groups satisfies Frisch's circularity condition (Frisch, 1936), so if we assume three groups A, B and C, then CDMI^{AB} x CDMI^{BC} = CDMI^{AC}.

[8] The CDMI does not assume convex combinations of group-specific frontiers to be feasible.

[9] The empirical application of this paper compares two school ownerships. However, this methodology could be applied to any other comparison of two or more groups of DMUs whose practices differ significantly. This methodology can also be used to follow through an impact evaluation program implemented in treated schools for comparison with the control group.

relevant implications for policy makers. The productivity change between *PGDS* and *PS* within *t* and *t+1* is defined as the pseudo-panel Malmquist index (PPMI) as follows:

$$PPMI_{t,t+1}^{GP} = \frac{CDMI_{t+1}^{GP}}{CDMI_{t}^{GP}} \tag{10}$$

Equation (10) indicates productivity gains between t and t+1 periods for *PGDS* (*G* group) with respect to *PS* (*P* group) when the index is higher than unity; $PPMI_{t,t+1}^{GP} > 1$ or productivity losses when is less than one; $PPMI_{t,t+1}^{GP} < 1$. If $PPMI_{t,t+1}^{GP} = 1$, then we conclude that the initial gap between both school groups computed in period t still remains in t+1.

Similarly, the PPMI can be decomposed into efficiency gap change (*EGC*) and technology gap change (*TGC*) calculating the ratio of the efficiency (technological) gap within the two periods for each school type, as Equation 11 shows:

$$PPMI_{t,t+1}^{GP} = \frac{CDMI_{t+1}^{GP}}{CDMI_{t}^{GP}} = \frac{EG_{t+1}^{GP}}{EG_{t}^{GP}} \cdot \frac{TG_{t+1}^{GP}}{TG_{t}^{GP}} = EGC_{t,t+1}^{GP} \cdot TGC_{t,t+1}^{GP}, \tag{11}$$

where EG_{t}^{GP} (EG_{t+1}^{GP}) and TG_{t}^{GP} (TG_{t+1}^{GP}) represent efficiency and technological gaps among *PGDS* and *PS* at period *t* (*t+1*), respectively. If $EGC_{t,t+1}^{GP} > 1$ ($TGC_{t,t+1}^{GP} > 1$) would imply that the efficiency (technological) gap is wider -favoring PGDS- in period *t+1* than *t*. The PPMI for two groups satisfies the circular relationship so $PPMI_{t,t+2}^{GP} = PPMI_{t,t+1}^{GP} x \, PPMI_{t+1,t+2}^{GP}$. This property is demonstrated through Equation (12) as follows:

$$\frac{CDMI_{t+2}^{GP}}{CDMI_{t}^{GP}} = \frac{CDMI_{t+1}^{GP}}{CDMI_{t}^{GP}} \cdot \frac{CDMI_{t+2}^{GP}}{CDMI_{t+1}^{GP}} \tag{12}$$

2.4. Matching of representative school samples and confidence intervals.

A significant challenge for applying the PPMI is how to match two representative samples with different sample sizes[10]. The traditional Malmquist index can be estimated using unbalanced samples but, in this case, the CDMI would be built without the performance information of unmatched units. Therefore, all available information is used to estimate each annual production

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[10] The sample sizes required to correctly represent the two populations compared normally varies due to different population sizes.

frontier in order to evaluate other units. However, information on the distances of unmatched DMUs to the other group technology is not included in geometric averages to calculate the CDMI.

The most common situation for empirical purposes is that *PS* and *PGDS* have a different sample size (N and M respectively). We propose two alternatives for obtaining robust matches of different representative units for two groups in the same period.

Alternative 1 (Camanho and Dyson, 2006)

Alternative 1 was used first by Camanho and Dyson (2006). In their empirical application they ran the CDMI with different group sizes. Let us assume that $N > M$. In this case, we randomly select M units from the largest sample N, where the remaining units are used to build the production frontier but are not considered in order to output the CDMI. As Camanho and Dyson (2006) recognize, there may be an unaccounted-for group size effect, although it is expected to be insignificant when both groups have similar sizes[11]. For this reason, when sample sizes are similar, we suggest applying this method and matching both samples randomly; for example, when $\frac{N}{M} < 2$.

Alternative 2

In this paper we propose a second alternative, which consists of adding a number of units to the smaller sample to obtain the same number of units as in the larger one. Let us assume that $N > M$ and then:

- Choose a natural number f equal to or greater than two ($f = 2, 3, \ldots, F$) to minimize the difference $M{*}f - N \geq 0$.
- Then, $M{*}f - N$ units are randomly removed from the $M{*}f$ sample to equal N.

This method has the advantage of using all available information and not discarding the valuable performance information from a large number of DMUs from the bigger group[12].

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[11] They also propose bootstrap (p. 41), which they did not apply in their paper as their main aim was to illustrate the applicability of the proposed index.

[12] Many other methods could be used to reduce this ‘different size effect’; however this line is left for future research.

2.5. Confidential Intervals

Färe *et al.* original Malmquist index (1992) measures productivity and its components change over time using the ratio of two output (input) distance functions. However, this approach is unable to test if the estimated changes in productivity and its components are significantly different from one. On the other hand, the Malmquist index is calculated using a non-linear programming technique, like, for example, data envelopment analysis (DEA), so the true production frontier is actually unknown and, consequently, the results of applying this approach are not statistically supported.

Thus, two main alternatives may be used in our theoretical framework in order to deal with this problem: the bootstrap methodology and a Monte-Carlo procedure. Both tools are widely useful to obtain the confidence intervals for the Malmquist indices, although the process is different for each approach. Bootstrapping was proposed by Simar and Wilson (1999), who focus their strategy on the replication of the unobserved data-generating process. On the other hand, the Monte Carlo procedure consists of obtaining a finite number of pairings and afterward calculating a CDMI index for each pairing. For the sake of simplicity, we follow Simar and Wilson*'s* bootstrap methodology (1999), although a similar analysis could be done using a Monte Carlo experiment. To the best of our knowledge, this bootstrap procedure (Simar and Wilson, 1999) has not been previously used in high schools, although Parteka and Wolszczak-Derlacz (2013) apply it to higher education at country level.

The estimation of the distance functions contained in Equation 5 may be computed solving different linear programs. Then, the bootstrapping consists of assuming a data-generating process for each distance calculation through DEA and replicating it in a large enough number *B* of pseudo-samples. Hence, bootstrapping involves replicating this data-generating process; generating an appropriately large number *B* of pseudo samples from the original sample for each bootstrap replication, and applying DEA to these pseudo samples in order to calculate the distances required to compute the CDMI in Equation 5.

Finally, after computing the bootstrap estimation, it is possible to calculate the confidence intervals at the desired significance level by approximating the unknown distribution of the $CDMI_t^{GP}$ using the bootstrap values, $\left\{CDMI_t^{GP*B}\right\}_{b=1}^{B}$. Then, after a large enough number of bootstrap replications, $B \to \infty$, we get a confidence interval allowing us to conclude if the CDMI is different from one[13].

3. THE EDUCATIONAL PRODUCTION FUNCTION, DATASET AND VARIABLES

In our empirical analysis, we use Spanish data from *PISA* 2003, 2006 and 2009, which provide data on 15-year-old students from three Spanish regions that opted to enter an extended representative sample of their population for this assessment 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 entirely responsible for the educational resources management since 2000. Publicly funded schools in Spain, i.e., schools receiving their core funding from the government agencies, may be classified as either *PS* or *PGDS*. The difference lies on whether a public entity or a private agency, respectively, has decision-making authority concerning their management. *PS* are monitored and managed by a public education authority or agency. *PGDS* are governed by a non-public organization[14], which implies that their governing board is not elected by a government agency. Private schools are classified as *PGDS* if they receive more than 50% of their core funding from government agencies[15].

One of the main advantages of the *PISA* study is that it does not evaluate cognitive abilities or skills using a single score; instead each student receives a score in each test on a continuous scale. This way, *PISA* attempts to account for the effect of particular external conditioning factors that do not depend on the students when taking the test, namely being ill or very nervous, among other random factors. Furthermore, it also means that the measurement error in education is not independent of the position of the student in the distribution of results. Hence, students with very low or high results have higher associated measurement errors and higher asymmetry in the error distribution.

Likewise, *PISA* also collects a large set of data on these variables from two questionnaires: one completed by the students themselves and another filled out by the principals. From these data, it is possible to extract information referred to the main determining factors of educational

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[13] A more detailed explanation may be found in Simar and Wilson (1999). $CDMI_{t+1}^{GP}$, $CDMI_{t}^{GP}$ and $PPMI_{t,t+1}^{GP}$ and their components are calculated B = 2,000 times. After that, confidence intervals are built with a 90%, 95% and 99% significance (α=0.1; α=0.05; α=0.01, respectively). This is done by sorting the index values and deleting ((α/2)*100) per cent of the highest and lowest values from the sorted sample).

[14] Most of these organizations are Catholic schools, teachers' cooperatives, non-profit organizations or simply private enterprises.

[15] There are also government-independent private schools, controlled by non-government organizations which receive most of their core funding from students fees. In this paper, we focus only on the publicly funded schools.

performance represented by variables associated with the family and the educational environments, as well as with the school management and the educational supply.

The educational production function

Many earlier papers on economic of education, the common conceptual framework for estimating the educational production function might take the following form (Levin, 1974; Hanushek, 1979):

$$A_i^t = f(B_i^t, S_i^t), \tag{13}$$

where A_i^t is the output (y_i^t in Equation 1) that now equals the average achievement of students attending school *i* at time *t*; B_i^t is the school's average socio-economic background and S_i^t are average school resources. Both, B_i^t and S_i^t are the input components of x_i^t in Equation 1. This production function may be estimated assuming the existence of inefficient behaviors in schools (Nechyba, 2000; Woessman, 2001), as Equation (9) express:

$$A_i^t = f\left(B_i^t, S_i^t\right) \cdot\, u_i^t \tag{14}$$

where $u_i^t = D_i^t\left(x_i^t, y_i^t\right)$, as defined in Equation (1) for school *i*.

Outputs

The true output as result of an individual's education is very difficult to measure empirically due to its inherent intangibility. Education is not just about being able to repeat information and answer questions; it is also concerned with the ability to interpret the information and 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 students' results in the three vehicular competences evaluated in PISA (Mathematics, Reading and Science) as the school output.

Inputs

In order to calculate the Malmquist index we use four inputs directly involved in the learning process.

- *PARED* is the index of the highest level of parental education, measured by the number of years of schooling according to the International Standard Classification of Education (ISCED, OECD, 1999).
- *HISEI* is the index of the highest parental occupational status according to International Socio-Economic Index of Occupational Status (ISEI, Ganzeboom *et al*., 1992).
- *SCHRESOURCES* is an index of the quality of the school resources derived from school principal responses. All questionnaires contain several items related to school deficiencies regarding such issues, but some items are different across the three waves. So ten coincident items were selected for each sample, and the school receives one point for each item for which the principal's response is *not deficient*[16]. The maximum (minimum) punctuation for each school is ten (zero) points, which indicates an excellent (dreadful) educational input[17].
- *STRATIO* is a ratio between the total number of teachers weighted by their dedication (part-time teachers contribute 0.5 and full-time teachers 1) and the total number of students in the school.

Tables 1-3 show the mean values for the three outputs –students' results in Mathematics, Reading and Science- and for the above inputs. The figures below indicate that the students' results are generally higher for students attending *PGDS*, for all disciplines and regions, being these differences larger among Basque Country schools. Nevertheless, the average socioeconomic background, measured by the variables *PARED* and *HISEI,* is normally lower in *PS*. Similarly, *PGDS* have higher quality resources, *SCHRESOURCES*, although the student-teacher ratio (*STRATIO*) benefits *PS*, where the ratio is higher, which implies that each teacher is in charge of a smaller group of students. This advantage of PS may be due to multiple factors related with Spanish educational regulation. Main factor may be that the number of instruction hours for pupils in *PS* is wide smaller than in *GDPS*, so private organizations reduce their expenditures by reducing class size (student-teacher ratio)[18].

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[16] The selected items are: 'Qualified science teachers', 'Qualified mathematics teachers', 'Qualified reading teachers', 'Any other personal support', 'Science laboratory equipment', 'Educational material', 'Computers', 'Software', 'Library resources', 'Audiovisual resources'. This variable is subjective and for this reason is only a *proxy* of a more realistic 'physical school resources' variable.

[17] This variable has been rescaled so the minimum value is one in order to avoid zeros in the empirical analysis.

[18] For a wide explanation about the class size differences, see "Education at a Glance 2013, OECD Indicators.

Consequently, *PS* needs a higher number of teachers to reach similar educational objectives than GDPS. On the other hand, it is a fact that *GDPS* tend to be located in higher population cities, ensuring this way educational attendance. In fact, only public organizations are placed in rural areas, which takes special relevance on the Spanish case, so there are many cities with a very low density population.

Table 1: ***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 (PS)*											
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
Obsv.	29				31				31			
Variables	*Private Government-Dependent Schools (PGDS)*											
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
Obsv.	15				17				14			

Source: Own compilation from PISA 2003, 2006 and 2009

Table 2: ***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 (PS)*											
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
Obsv.	25				29				24			
Variables	*Private Government-Dependent Schools (PGDS)*											
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
Obsv.	12				11				12			

Source: Own compilation from PISA 2003, 2006 and 2009

Table 3: ***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 (PS)*											
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
Obsv.	53				56				68			
Variables	*Private Government-Dependent Schools (PGDS)*											
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	580.10
Science	495.02	36.69	411.30	564.49	505.40	36.91	426.95	597.50	507.56	35.15	391.50	576.13
Pared	12.28	1.21	8.50	14.65	12.89	1.57	9.09	16.17	13.80	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	1.00	11.00	8.06	2.73	1.00	11.00	9.08	1.85	4.00	11.00
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
Obsv.	70				81				90			

Source: Own compilation from PISA 2003, 2006 and 2009

4. RESULTS

This section reports the main results of our analysis for the Spanish regions of Catalonia, Castile-Leon and Basque Country. Using our methodology, we can compare *PGDS* and *PS* productivity changes from 2003 to 2009.

Tables 4-11 report the results after applying the CDMI and PPMI approaches on 2003, 2006 and 2009 data considering the set of three outputs and four inputs. Table 4 shows the CDMI results in 2003, 2006 and 2009 using Alternative 1 to match the school samples. The first column for each year shows the CDMI, where *PS* are considered as period *t* and *PGDS* as period *t+1* as in Equation 5. After this measure, we report the main CDMI components: the efficiency gap (EG) and the technological gap (TG). Therefore, Table 5 indicates the 90%, 95% and 99% confidence intervals (Simar and Wilson, 1999) for the CDMI in each region and their components, *LB* being the lower bound and *UB* the upper bound of the interval. This confidence interval is useful statistically testing the different measures[19]. Tables 6 and 7 refer to the productivity gains between both *PS* and *PGDS* from 2003 to 2009 using Alternative 1 and their confidence intervals, respectively. The first column for each year of Table 6 shows the $PPMI_{t,t+1}^{GP}$ within two time periods followed by its components: the efficiency gap change (EGC) and the technological gap change (TG), respectively. Tables 8, 9, 10 and 11 replicate the analysis for each region using Alternative 2 to match both school type samples.

Tables 4 and 5 show the CDMI and its components for each period and region, using Alternative 1 to match the school samples and confidence intervals, respectively. The results from Table 4 indicate that PGDS are on average significantly more productive than PS in each period and for all three Spanish regions. Furthermore, differences in productivity are mostly explained by the technological difference between school ownership, especially for Basque Country where the technological difference among *PGDS* and PS was 41% in 2006.

Table 5 represents confidence intervals for all three time periods. From these results we may conclude whether the CDMI and its components are significantly different from one when the value one is not within the interval. Finally, in order to analyze the productivity changes in depth, we calculate the $PPMI_{t,t+1}^{GP}$ ratios and their components explained in Section 2.3. The results are shown in Tables 6 and 7. Table 6 points out that the average productivity evolution from 2003 to 2009 is not significant, so the initial gap measured by the CDMI remains. There is only a significant efficiency gap change in favor of *PS* in Castile-Leon.

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[19] Significant differences are showed in bold in Tables 4, 6, 8 and 10.

Results using Alternative 2 are available in Tables 8 and 9. Again, these results show that *PGDS* are significantly more productive than *PS* in all regions and periods. The results for both Alternative 2 and Alternative 1 are close, so we can conclude that, after bootstrap, both measurements are robust and yield similar conclusions. Finally, Tables 10 and 11 present the productivity gains by both school types from 2003 to 2009 and their confidence intervals for the PPMI and their components using Alternative 2. The results show a slightly better and significant productivity evolution for *PS* from 2003 to 2009 in Catalonia, where the productivity change is around 0.7%.

Moreover, the results show a persistent significant difference between *PS* and *PGDS* across the three waves. Two main ways, even a combination of both, to explain this result are the following. The first one is just to recall that private institutions and teachers employed in these enterprises have more incentives to make efficient use of resources then they are more productive in comparisons. The second way is related with the school choice (Crespo-Cebada *et al.*, 2014). Most Spanish families choose whether to send their children to a *PS* or a *GDPS* based on factors such as 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 teacher quality is higher in *PS* because they passed a competitive state exam to enter in the public school system. This is considered to possibly lead to a better overall academic achievement. On the other hand, teachers in *PS* are automatically granted tenure once they pass the entrance exam. This leads some people to argue that teachers in *PS* do not have clear incentives to improve their teaching methods once they enter the system.

However, there are two main possible explanations for slight self-selection of low socioeconomic background students in *PS*. The first reason is that *PGDS* may freely choose their location, being more disproportionally placed in middle, and high income neighborhoods where the expected profitability will be higher. On the other hand, generally *PGDS* education is more expensive than in *PS*. Mostly *PGDS* the use of the school uniform is mandatory and the educational materials, extra-curricular activities, the school bus or the lunch are more expensive than in *PS*.

However, it is unclear which the main factors explaining these performance differences are, but their existence warrants more research to monitor and correct this gap in the near future.

Table 4: CDMI. Alternative 1

		2003			*2006*			*2009*		
Region	*Statistic*	*CDMI*	*EG*	*TG*	*CDMI*	*EG*	*TG*	*CDMI*	*EG*	*TG*
Catalonia	*Mean*	***1.2077***	0.9963	***1.2018***	***1.1773***	1.0214	***1.1430***	***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
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
Basque Country	*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	0.027	0.0307	0.0111	0.0362

Significative differences at 90% level are highlighted in bold.

Table 5: Confidence interval for the CDMI. Alternative 1

Region	*Catalonia*						*Castile-Leon*						*Basque Country*					
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																	
CDMI	*1.1800*	*1.2602*	1.1756	1.2721	1.1682	1.288	*1.0852*	*1.1946*	1.0804	1.2062	1.0741	1.2352	*1.2193*	*1.2640*	1.2134	1.2776	1.2045	1.3059
EG	0.9736	1.0188	0.9682	1.0249	0.9565	1.0367	0.9831	1.0217	0.9785	1.0271	0.9683	1.0402	0.9796	1.0077	0.9758	1.0116	0.9697	1.0184
TG	*1.1710*	*1.2338*	1.1634	1.2433	1.1493	1.2630	*1.0722*	*1.1321*	1.0630	1.1420	1.0492	1.1594	*1.2287*	*1.2808*	1.2231	1.2935	1.2135	1.3304
	2006																	
CDMI	*1.1548*	*1.2255*	1.1511	1.2363	1.1464	1.2508	*1.1296*	*1.2116*	1.128	1.2163	1.125	1.2259	*1.3296*	*1.3964*	1.3156	1.4052	1.3004	1.4203
EG	1.0110	1.0324	1.0083	1.0363	1.0026	1.0438	0.9849	1.0062	0.9814	1.009	0.974	1.0145	0.9492	0.9875	0.9435	0.9934	0.9353	1.0037
TG	*1.1263*	*1.1622*	1.1216	1.1675	1.1117	1.1775	*1.1284*	*1.1556*	1.1253	1.1603	1.1192	1.1736	*1.3851*	*1.4553*	1.3766	1.4651	1.3605	1.4878
	2009																	
CDMI	*1.1732*	*1.2995*	1.1703	1.3051	1.1657	1.3139	*1.1058*	*1.2114*	1.1036	1.2213	1.1002	1.2414	*1.1926*	*1.2698*	1.1843	1.285	1.1708	1.3093
EG	0.9873	1.0126	0.9845	1.0173	0.9786	1.0250	1.0100	1.0431	1.0055	1.0472	0.9990	1.0575	0.9719	1.0006	0.9678	1.0044	0.9595	1.0125
TG	*1.1638*	*1.1984*	1.1565	1.2030	1.1450	1.2136	*1.0659*	*1.1177*	1.0599	1.1253	1.0503	1.1378	*1.2059*	*1.2985*	1.2003	1.3188	1.1878	1.3468

Table 6: Pseudo-panel Malmquist index. Productivity gains in *PS* and *PGDS* from 2003 to 2009. Alternative 1

		$PPMI^{GP}_{2003,2006}$			$PPMI^{GP}_{2006,2009}$			$PPMI^{GP}_{2003,2009}$		
Region	*Statistic*	*CDMI*	*EGC*	*TGC*	*CDMI*	*EGC*	*TGC*	*CDMI*	*EGC*	*TGC*
Catalonia	*Mean*	**0.9748**	1.0251	**0.9509**	1.0188	0.9786	**1.0337**	0.9966	1.0016	0.9917
	Std.Dev	0.0159	0.0191	0.0249	0.0191	0.0132	0.0166	0.0101	0.0100	0.0119
Castile Leon	*Mean*	**1.0270**	0.9932	**1.0372**	0.9863	**1.0312**	**0.9532**	1.0065	**1.0121**	0.9945
	Std.Dev	0.0178	0.0174	0.0224	0.0140	0.0151	0.0218	0.0092	0.0095	0.0138
Basque Country	*Mean*	**1.1012**	0.9750	**1.1328**	**0.8953**	1.0181	**0.8769**	0.9931	0.9964	0.9969
	Std.Dev	0.0192	0.0193	0.0235	0.0300	0.0187	0.0386	0.0142	0.0078	0.0170

Significative differences at 90% level are highlighted in bold.

Table 7: Confidence interval for PPMI (Alternative 1)

Region	*Catalonia*						*Castile-Leon*						*Basque Country*					
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*
	$PPMI^{GP}_{2003,2006}$																	
PPMI	0.9553	0.9939	0.9499	1.0001	0.9427	1.0106	1.0015	1.0491	0.9933	1.0540	0.9776	1.0642	1.0718	1.1299	1.0599	1.1375	1.0387	1.1529
EGC	1.0004	1.0520	0.9933	1.0593	0.9805	1.0737	0.9713	1.0155	0.9644	1.0215	0.9542	1.0333	0.9517	0.9991	0.9449	1.0049	0.9334	1.0174
TGC	0.9229	0.9808	0.9146	0.9882	0.8998	1.0036	1.0065	1.0676	0.9974	1.0777	0.9802	1.0941	1.0973	1.1704	1.0837	1.1804	1.0572	1.2015
	$PPMI^{GP}_{2006,2009}$																	
PPMI	0.9975	1.0541	0.9928	1.0643	0.9862	1.0739	0.9707	1.0053	0.9671	1.0105	0.9612	1.0246	0.8681	0.9298	0.8616	0.9414	0.8511	0.9638
EGC	0.9632	0.9949	0.9579	1.0003	0.9508	1.0111	1.0112	1.0516	1.0051	1.0582	0.9949	1.0683	0.9942	1.0431	0.9872	1.0513	0.9738	1.0633
TGC	1.0108	1.0559	1.0043	1.0617	0.9885	1.0731	0.9298	0.9815	0.9238	0.9895	0.9098	1.0034	0.8423	0.9184	0.8346	0.9332	0.8226	0.9594
	$PPMI^{GP}_{2003,2009}$																	
PPMI	0.9850	1.0120	0.9828	1.0179	0.9783	1.0240	0.9947	1.0179	0.9900	1.0210	0.9829	1.0270	0.9774	1.0128	0.9729	1.0196	0.9635	1.0306
EGC	0.9885	1.0148	0.9854	1.0184	0.9789	1.0249	1.0001	1.0246	0.9967	1.0284	0.9878	1.0348	0.9867	1.0064	0.9841	1.0093	0.9786	1.0140
TGC	0.9763	1.0067	0.9718	1.0108	0.9654	1.0185	0.9779	1.0121	0.9725	1.0176	0.9644	1.0285	0.9774	1.0204	0.9719	1.0281	0.9591	1.0404

Table 8: CDMI. Alternative 2

		2003			*2006*			*2009*		
Region	*Statistic*	*CDMI*	*EG*	*TG*	*CDMI*	*EG*	*TG*	*CDMI*	*EG*	*TG*
Catalonia	*Mean*	***1.1838***	**0.9835**	***1.1874***	***1.2014***	1.0181	***1.1753***	***1.2006***	**0.9829**	***1.2031***
	Std.Dev	0.0387	0.0097	0.0147	0.0181	0.0094	0.0196	0.0422	0.0075	0.0111
Castile Leon	*Mean*	***1.1262***	**0.9865**	***1.1307***	***1.1526***	0.9989	***1.1403***	***1.1226***	1.0006	***1.1039***
	Std.Dev	0.0290	0.0104	0.0197	0.0325	0.0077	0.0100	0.0438	0.0086	0.0191
Basque Country	*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

Significative differences at 90% level are highlighted in bold.

Table 9: Confidence interval for CDMI. Alternative 2

Region	*Catalonia*						*Castile-Leon*						*Basque Country*					
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																	
CDMI	*1.1568*	*1.2645*	1.1539	1.2739	1.1492	1.291	*1.1007*	*1.1767*	1.0978	1.1857	1.0925	1.2104	*1.2350*	*1.2887*	1.2239	1.303	1.2096	1.3308
EG	0.9710	0.9959	0.9679	0.9994	0.9617	1.0063	0.9732	0.9999	0.9694	1.0033	0.9625	1.0097	0.9888	1.0151	0.9861	1.0191	0.9805	1.0264
TG	*1.1707*	*1.2080*	1.1658	1.2149	1.1582	1.2265	*1.1083*	*1.1584*	1.1029	1.1684	1.0926	1.1871	1.2387	1.2944	1.2341	1.3097	1.2233	1.3402
	2006																	
CDMI	*1.1812*	*1.2265*	1.1789	1.2327	1.1751	1.256	*1.1312*	*1.2215*	1.1293	1.2273	1.1255	1.2399	*1.3279*	*1.3898*	1.3149	1.3948	1.3023	1.4069

EG	1.0062	1.0296	1.0019	1.0320	0.9920	1.0363	0.9887	1.0086	0.9856	1.0105	0.9786	1.0137	0.9668	1.0009	0.9624	1.0067	0.9554	1.0142
TG	*1.1552*	*1.2029*	1.1529	1.2129	1.1474	1.2388	*1.1288*	*1.1529*	1.1265	1.1585	1.1225	1.1700	*1.3630*	*1.4219*	1.3561	1.4317	1.3448	1.4482
	2009																	
CDMI	*1.1758*	*1.2944*	1.1741	1.2993	1.1707	1.3083	*1.0906*	*1.2105*	1.0882	1.2220	1.0846	1.2453	*1.1936*	*1.2618*	1.1823	1.2754	1.1718	1.3064
EG	0.9732	0.9920	0.9703	0.9943	0.9637	0.9999	0.9891	1.0114	0.9861	1.0140	0.9794	1.0198	0.9821	1.0086	0.9783	1.0124	0.9709	1.0189
TG	*1.1901*	*1.2174*	1.1864	1.2228	1.1800	1.2312	*1.0831*	*1.1328*	1.0796	1.1393	1.0737	1.1516	*1.1990*	*1.2794*	1.1941	1.2951	1.1818	1.3258

Table 10: Pseudo-panel Malmquist index. Productivity gains in *PS* and *PGDS* from 2003 to 2009. Alternative 2

		Ratio 03-06			*Ratio 06-09*			*Ratio 03-09*		
Region	*Statistic*	*PPMI*	*EGC*	*TGC*	*PPMI*	*EGC*	*TGC*	*PPMI*	*EGC*	*TGC*
Catalonia	*Mean*	1.0149	**1.0351**	0.9896	0.9985	**0.9653**	1.0235	**1.0070**	0.9997	1.0065
	Std.Dev	0.0265	0.0129	0.0206	0.0279	0.0125	0.0184	0.0052	0.0062	0.0077
Castile Leon	*Mean*	**1.0232**	1.0125	1.0084	**0.9735**	1.0017	**0.9678**	0.9981	1.0070	0.9879
	Std.Dev	0.0151	0.0129	0.0191	0.0172	0.0116	0.0196	0.0114	0.0067	0.0123
Basque Country	*Mean*	**1.0805**	0.9820	**1.1013**	**0.8970**	1.0111	**0.8855**	0.9846	0.9966	0.9878
	Std.Dev	0.0177	0.0172	0.0221	0.0267	0.0168	0.0347	0.0133	0.0071	0.0162

Significative differences at 90% level are highlighted in bold.

Table 11: Confidence interval for PPMI. Alternative 2

Region	*Catalonia*						*Castile-Leon*						*Basque Country*					
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																	
PPMI	0.9686	1.0449	0.9595	1.0519	0.9430	1.0615	1.0028	1.0422	0.9938	1.0476	0.9826	1.0567	1.0547	1.1055	1.0452	1.1112	1.0229	1.1232
EGC	1.0174	1.0523	1.0125	1.0573	1.0024	1.0681	0.9957	1.0302	0.9909	1.0337	0.9813	1.0429	0.9609	1.0041	0.9552	1.0096	0.9459	1.0188
TGC	0.9661	1.0169	0.9587	1.0271	0.9471	1.0432	0.9824	1.0321	0.9748	1.0379	0.9598	1.0517	1.0689	1.1346	1.0566	1.1443	1.0331	1.1605
	Ratio 2006-2009																	
PPMI	0.9703	1.0561	0.9644	1.0664	0.9557	1.0750	0.9555	0.9960	0.9512	1.0035	0.9425	1.0179	0.8731	0.9276	0.8667	0.9388	0.8589	0.9606
EGC	0.9510	0.9804	0.9471	0.9850	0.9402	0.9953	0.9866	1.0167	0.9824	1.0212	0.9765	1.0297	0.9897	1.0331	0.9832	1.0397	0.9705	1.0521
TGC	0.9974	1.0462	0.9885	1.0511	0.9691	1.0594	0.9455	0.9946	0.9410	1.0012	0.9302	1.0122	0.8540	0.9240	0.8461	0.9372	0.8331	0.9608
	Ratio 2003-2009																	
PPMI	1.0004	1.0137	0.9979	1.0153	0.9930	1.0185	0.9849	1.0139	0.9810	1.0192	0.9735	1.0272	0.9700	1.0019	0.9650	1.0073	0.9538	1.0200
EGC	0.9919	1.0077	0.9897	1.0102	0.9851	1.0142	0.9984	1.0160	0.9962	1.0182	0.9914	1.0225	0.9875	1.0056	0.9849	1.0083	0.9802	1.0128
TGC	0.9961	1.0163	0.9933	1.0192	0.9870	1.0242	0.9733	1.0040	0.9692	1.0083	0.9599	1.0175	0.9695	1.0093	0.9642	1.0155	0.9520	1.0275

5. CONCLUSIONS

The Malmquist Index methodology is widely used in the literature in order to measure 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 over time.

In this paper, we extend the Malmquist-type index proposed by Camanho and Dyson (2006) that is used to measure the average productivity divergences between different groups of DMUs within the same year. Thus, a pseudo-panel Malmquist index is built for comparing the evolution of average productivity discrepancies between publicly funded schools, including both public and government-dependent private schools, when only a pseudo-panel database is available. This new index is especially useful for comparing students and school behaviors using different waves of international databases like PISA or TIMSS.

To do this, we use school data from PISA 2003, 2006 and 2009 that provide us with a wide range of information about the educational context in three Spanish regions: Castile-Leon, Catalonia and Basque Country. Moreover, two different approaches to pairing school samples are developed in order to check the robustness of the results under different matching alternatives. Finally, we take Simar and Wilson’s approach (Simar & Wilson1999) to obtain confidence intervals for the Malmquist indices and their components using the bootstrap methodology.

The main results of our analysis can be summarized as follows. Firstly, private government-dependent schools are persistently more productive than public schools in each individual period. Thus, irrespective of the alternative used to match different school type samples, *PGDS* generally outperform PS on average, due to *PGDS’s* technological superiority. This means that within-group technical efficiency variance is on average similar in both groups, so there will be good and bad schools inside each group. However, the best schools that define the most productive frontier are located in the PGDS group. Secondly, the average productivity evolution from 2003 to 2009 is flat, so the initial differences are still there after the six-year period. Finally, CDMI is built using the DEA methodology to obtain the distance of each unit to the frontiers, so public schools are penalized on the grounds of a better input endowment compared with PGDS.

To conclude, we think that this procedure should be used to further monitor the educational system in order to detect best practices, analyze the pedagogical characteristics inside the school black box and guarantee equality of educational opportunities for all students attending publicly funded schools. This methodology can be also used in impact evaluation programs as a method to capture more information to explain the traditional average performance difference between the treated and non-treated group.

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