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EFFICIENCY OF SECONDARY SCHOOLS IN ECUADOR: A VALUE BASED DEA APPROACH

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Abstract

This paper proposes a novel Value-Based Data Envelopment Analysis (VBDEA) model which specifically tackles non-discretionary data to assess the performance of 159 secondary schools from Ecuador by employing data from the Programme for International Student Assessment for Development (PISA-D). The factors considered to perform the efficiency assessment of each school include an index, which reflects the quality of basic school infrastructures and instruction resources, the economic, social and cultural level index of students, the student-teacher ratio, and test scores in maths, reading and science. Overall, our findings suggest that the average efficient school has mean scores across all competences above the scores attained by the average national school, but below the average of Latin American and Caribbean countries. In addition, schools operating with the lowest efficiency scores usually need to make a greater effort to improve results in maths when compared to reading and science competences. Finally, schools more often selected as a reference in terms of best practices, and which are classified as robust in terms of efficiency, are not necessarily performing with high test results.

Keywords: Value Based Data Envelopment Analysis; Non-discretionary factors; Multicriteria Decision Analysis; Ecuadorian Secondary Schools.

1. Introduction

The efficiency assessment of the educational sector is of paramount importance, particularly in the current COVID-19 turmoil, since public resources are scarce and compete with other public expenses, namely the health sector. This is particularly relevant in countries like Ecuador (the focus of this paper) where the investment in education, relative to GDP, has almost doubled in the last decade (2008-2018), going from 3% to 5% along that period, although far from other Latin American countries, as Costa Rica, Chile, Perú or Colombia, whose investment in education with respect to the total budget, rose between 15% to 23% by 2018 (in Ecuador the figure was 13%)[1]. Hence, the efficiency assessment of the educational system is a key issue in developing countries, where finding a balance between efficacy and resources is particularly challenging.

The efficiency assessment of public education has attracted much attention over the years, being a relevant part of the political agenda in numerous countries. A thorough review of studies dedicated to this topic might be found in Jonhes (2015) and De Witte and López-Torres (2017).

In this context, Data Envelopment Analysis (DEA) can be of value because it enables to encompass into an aggregate measure of efficiency the multiple factors (resources and outcomes) used towards educational assessment, thus providing better support to policy decision makers – DMs (Henriques and Marcenaro, 2021). Besides, the DEA approach has been broadly used in the appraisal of the efficiency of the educational sector, corresponding to one of its top fields of application (Emrouznejad et al., 2008; Liu et al., 2013; Emrouznejad & Yang, 2018).

Nevertheless, to the best of our knowledge, none of the studies published so far and revised in these works particularly accounted for the translation of the DMs' preferences into value functions in the efficiency assessment of the educational system. This particular aspect is relevant, namely when the factors under evaluation have negative or null values (see e.g., the economic, social and cultural level index). To overcome this issue, in this study we employ the VBDEA methodology, which jointly combines the application of DEA with Multiple Criteria Decision Aiding (MCDA), accounting for the main indicators (resources and outcomes) that might influence schools' efficiency (Gouveia, Dias, & Antunes, 2008).

[1] INEVAL (2019).

When compared to the typically used DEA models, VBDEA has distinctive features since it translates the inputs (resources) and outputs (outcomes) into value scales. Besides, this approach is specifically suited for incorporating into the analysis the preferences of the DMs, either by considering value functions or by allowing for the introduction of weight constraints according to the main concerns of the DMs, and easily allows tackling negative or null data. In addition, this approach also entails a procedure which allows performing the robustness assessment of the results obtained, enabling the DMs to comprehend how sensitive the efficiency of each school to data variation is. This technique is mainly important to evaluate how changes in factors with intra-school variability (e.g., those related to students, like test scores and the economic, social and cultural level index), might affect the schools' efficiency scores.

In spite of its usefulness in a broad range of contexts (e.g., Gouveia, Dias, Antunes, Boucinha, & Inácio, 2015; Gouveia, Dias, Antunes, Mota, Duarte, & Tenreiro, 2016; Gouveia, Neves, Dias & Antunes, 2018; Gouveia, Henriques & Costa, 2021), the VBDA approach has not thus far been used in the efficiency assessment of schools.

Finally, since there is a lack of scholarly attention regarding the global population of Ecuadorian schools by means of DEA and simultaneously there are no studies based on the most recent Programme for International Student Assessment for Development (PISA-D) data, an empirical application is suggested which explores the use of the VBDA approach in the evaluation of Ecuadorian secondary schools' efficiency. Specifically, PISA-D includes, among others, the following new features and enhancements aimed at making the PISA assessment more accessible and relevant to middle and low-income countries (OECD, 2018b): a) an equal treatment of the three major domains tested: reading, mathematics and science (unlike PISA, where one of the domains is given a particular focus in each cycle); b) targeted test instruments that cover a wider range of performance at the lower levels of proficiency (unlike PISA where the tests are not targeted on particular levels of performance); c) modified test instruments and questionnaires that have a reduced reading burden, in recognition of the lower levels of reading literacy capacity in middle- and low-income countries; d) several distinct PISA-D items that are more relevant to middle- and low-income countries.

In this context, this study presents the following novelties: a) it employs VBDEA to the efficiency assessment of schools in Ecuador; b) establishes a new way of handling non-discretionary data in VBDA; c) incorporates the preferences of a hypothetical DM, by considering value functions inspired by the value function of Kahneman and Tversky

(1979), for factors with positive and negative values – e.g. the index of socioeconomic status; d) performs the robustness assessment of the results obtained, particularly in face of factors with intra-school variability; e) it considers different scenarios through the introduction of constraints on the weights, thus contemplating a scenario revealing a DM more concerned with maths scores and another one focusing on reading scores.

The outline of this paper is provided as follows: Section 2 delivers a literature review of studies devoted to the appraisal of the educational system in Ecuador. Section 3 further describes the VBDA approach, specifically considering the introduction of non-discretionary data; Section 4 explains the main presumptions concerning the data employed; Section 5 discusses some results; and Section 6 draws some conclusions.

2. Literature review

The first documented research on the efficiency of Ecuador's educational system was published by Ponce (2000). This study uses cohort analysis for evaluating the internal efficiency of Ecuador’s educational system by measuring the number of years that students take to attain a certain level of education. Later, Ponce (2008) also assessed the effect of conditional economic transfers on the enrolment rate and learning outcomes in schools in rural Ecuador. In the same vein, Schady & Araujo (2008) evaluated the impact of a money transfer program in Ecuador, the Human Development Bonus, on school enrolment.

A fairly extensive study was also carried out by Arcos Cabrera & Vásconez (2008), in which they investigate the efficiency of the secondary school system. Towards this end, their study uses the enrolment and promotion of students, the repetition rate, the rate of school survival and academic achievements in maths and language.

Other lines of research address the influence of teachers on learning outcomes (e.g., Araujo, Carneiro, Cruz-Aguayo, & Schady (2016) and Cruz-Aguayo, Ibarrarán, & Schady (2017)), whereas other studies focus on school segregation (e.g., Murillo & Martínez-Garrido (2017) and Carrillo (2020)).

Recently, Ponce & Drouet, (2017) and Ponce & Intriago (2017) published reports which evaluate the impacts of specific programs implemented by the government, such as the so-called “millennium schools” and that of “international baccalaureate”, respectively, in both cases using educational outcomes through difference in differences models.

A prolific number of studies with respect to Ecuador's education system can be found in the reports of international assessments in which the country's students have participated using multilevel models to explain the learning outcomes achieved – see for example the Second Regional Comparative Study, in which the countries of Latin America (UNESCO-OREALC, 2010) participate, and the reports of the Third Regional Comparative Study (UNESCO-OREALC, 2017; UNESCO-OREALC, 2016b; UNESCO-OREALC, 2015; UNESCO-OREALC-BID, 2017; UNESCO-OREALC, 2016a).

With regard to the analysis of PISA's outcomes for development, there are only the reports issued by the OECD and the Ecuador Educational Assessment Institute (OECD, 2018b; OECD, 2018b; OECD, 2018c; INEVAL, 2018). Other publications refer to the political process by which the different countries participating in PISA-D, were incorporated into this program (Addey, 2017; Addey & Sellar, 2018, Addey, 2019).

From the literature review described herein it can be ascertained that there are no studies which address the efficiency assessment of schools in Ecuador through the DEA methodology. As in a broad range of studies which employ PISA data (see e.g., Henriques & Marcenaro, 2021; Aparicio et al. (2018, 2019); Agasisti & Zoido, 2018; Agasisti, 2013), this type of methodologies can be particularly insightful when resorting to the recent data released by PISA-D.

Hence, we will specifically address the efficiency assessment of secondary schools in Ecuador through the application of VBDA, employing the most recent data available in PISA-D.

3. The methodological approach

The next sections provide a description of the main underpinning assumptions regarding the VBDA methodological approach used herein.

3.1. The VBDEA approach with non-discretionary factors

The VBDEA method was originally proposed to overcome some of the well-known shortcomings of the Additive DEA model, using concepts from the Multi-Attribute Value Theory (MAVT) with imprecise information (Gouveia et al., 2008). The scale problem arises in the additive DEA model because the projection of the inefficient DMUs onto the efficient frontier depends on the scales used to measure each input or output. Another problem is that the performance in some factors (inputs or outputs) often presents negative values. Finally, the efficient measurement is very pessimistic, since the L_1 distance is being maximized and this efficiency measure does not have an intuitive interpretation.

In this novel approach, each criterion (input or output) is converted into partial value functions, each of them defined in the range [0,1], usually obtained by considering the preferences of a DM. The worst performance in each criterion has the value 0, and the best performance has the value 1, resulting in the maximization of all the criteria. Subsequently, the additive value functions are used to aggregate the partial value functions associated with each criterion, based on the MAVT (Keeney & Raiffa, 1976). This overcomes the problem of scales since all input and output measures are translated into values. In addition, the weights used in the aggregation take on a specific significance as the coefficients of the value functions that define the direction of the projection. These weights are chosen to benefit each DMU as much as possible. Finally, the efficiency measure of each DMU will have an intuitive meaning associated with the "minimum-maximum regret" rule.

Considering that each DMU of the sample set $\{DMU_j : j = 1, \dots, n\}$ is evaluated on m factors (criteria) to be minimized x_{ij} $(i = 1, \dots, m)$ and p factors (criteria) to be maximized y_{rj} $(r = 1, \dots, p)$, the factors are converted into partial value functions $\{v_c(DMU_j), c = 1, \dots, q, \text{with } q = m + p,\ j = 1, \dots, n\}$ and aggregated in a global value function taking into account the additive MAVT model, $V(DMU_j) = \sum_{c=1}^{q} w_c v_c\,(DMU_j)$, where $w_c \geq 0$, $\forall c = 1, \dots, q$ and $\sum_{c=1}^{q} w_c = 1$ (by convention). The scale coefficients $w_1, \dots, w_q$ are the weights of the value functions and reflect the value trade-offs of the DM. Each DMU can choose its weights in order to minimize the distance to the best DMU, in the spirit of the "min-max regret" rule.

The min-max regret rule compares the alternatives (DMUs) based on the greatest difference, taking into account all acceptable vectors of the scale coefficients (weights), with the optimal alternative (DMU) for this vector.

The maximum regret associated with a given DMU is the maximum loss of opportunity associated with the choice of that DMU, i.e, $R_{max}(DMU_k) = \max_{w}\left\{\left(\max_{j \neq k} v(DMU_j)\right) - v(DMU_k)\right\}$. The DMUs with the minimum value are preferred.

In the original VBDEA (Gouveia et al 2008, 2013) model it is assumed that all factors (inputs and outputs) are converted into value functions and that they can be varied at the discretion of management, assuming that all the inefficient DMUs reflect bad management decisions. These factors are usually designated as “controllable”. However, the performance of those inefficient DMUs might be underestimated, since there might exist “uncontrollable” factors, which are not under management’s control.

In the case of educational policies, there are some undesirable inputs (viewed as criteria in the VBDEA model) that cannot be avoided. For example, ”minority”, ”economically disadvantaged” and “low English proficiency” students might be regarded as undesirable, which are clearly non-controllable (Cooper, Seiford, & Tone, 2007). The low rate of attendance can also be perceived as an undesirable input, but in this latter case it can be controlled (Rivkin, Hanushek, & Kain, 2005; Tavana, Ebrahimnejad, Santos-Arteaga, Mansourzadeh, & Matin 2018).

Hence, for the purpose of considering non-discretionary factors, the VBDEA model needs to be changed in Phase 1.

Let D be the set of discretionary factors and ND the set of non-discretionary factors. After converting all the factors (inputs and outputs) into value scales, problem (1), resulting from Phase 1, is solved.

$$\min_{d_k,w} d_k$$

$$s.t. \sum_{c=1}^{q} w_c v_c(DMU_j) - \sum_{c=1}^{q} w_c v_c(DMU_k) \leq d_k, j = 1, \ldots, n; j \neq k \qquad (1)$$

$$\sum_{c=1}^{q} w_c = 1, c \in D$$

$$w_c \geq 0, \forall c = 1, \ldots, q$$

$$w_c \leq 1, \forall c \in ND$$

If a DMU has a non-negative score, d_k^*, then the DMU is inefficient and a target can be computed solving linear problem (2), taking into account discretionary (D) and non-discretionary factors (ND):

$$\min_{\lambda,s} z_k = -\sum_{c=1}^{q} w_c^* s_c$$

$$s.t. \sum_{j=1, j\neq k}^{n} \lambda_j v_c(DMU_j) - s_c = v_c(DMU_k), c = 1, \ldots, q \qquad (2)$$

$$\sum_{j=1, j\neq k}^{n} \lambda_j = 1$$

$$\lambda_j, s_c \geq 0, j = 1, \dots, k-1, k+1, \dots, n; \ c = 1, \dots, q$$

A convex combination of the value score vectors associated with the n-1 DMUs is expressed by the variables λ_j, j=1,…,k-1,k+1,…,n. The set of efficient DMUs (it could be a single one) that define the convex combination with λ_j >0 are called the "peers" of DMU k under evaluation. This convex combination corresponds to a point on the efficient frontier that is better than DMU k by a difference of value of s_c (slack) in each criterion c.

The phases of the VBDA model are briefly described next:

Phase 1: Compute the efficiency measure, d_k^*, for each DMU, $k = 1,...,n$, and the corresponding weighting vector w_k^* by solving linear problem (1), excluding the weights of the non-discretionary factors of the convexity constraint.

Phase 2: If $d_k^* \geq 0$ then solve the "weighted additive" problem (2), using the optimal weighting vector resulting from Phase 1, w_k^*, and determine the corresponding projected point of the DMU under evaluation.

The solution obtained in Phase 1, d_k^* , for each DMU k ($k = 1,...,n$) is the distance defined by the value difference to the best of all DMUs (note that the best DMU will also depend on w), excluding itself from the reference set. If d_k^* is negative, then the DMU k under evaluation is efficient, which admits the discrimination of the efficient DMUs, as in the Andersen and Petersen´s (1993) super-efficiency model.

3.2. Robustness analysis with non-discretionary factors

Several real problems solved with DEA models do not take into account the uncertainty in the data. The assessment of the robustness of the DMUs is mainly important in this work to evaluate how changes in factors with intra-school variability might impact the scores of efficiency.

Since the VBDEA is a non-oriented model (Gouveia et al., 2013), problems of infeasibility do not arise. The robustness analysis is carried out considering that the perturbations in the coefficients of factors with intra-school variability are within an interval.

If p_{cj} is the original performance of factor c for DMU_j considered as uncertain but bounded within the range $p_{cj}^L \leq p_{cj} \leq p_{cj}^U$ for a given tolerance δ applied to all performances, then we established that $p_{cj}^L = p_{cj}(1-\delta) \leq p_{cj} \leq p_{cj}(1+\delta) = p_{cj}^U$. Considering that the value functions $v_c(.)$ are increasing for factors to be maximized and decreasing for factors to be minimized, let $v_c^L(DMU_j)$ and $v_c^U(DMU_j)$ denote, respectively, the lowest and highest value obtained by DMU_j for the given tolerance interval:

$$v_c^L(DMU_j) = \begin{cases} v_c\left(p_{cj}(1-\delta)\right), & if\ c\ is\ being\ maximized \\ v_c\left(p_{cj}(1+\delta)\right), & if\ c\ is\ being\ minimized \end{cases}$$

$$v_c^U(DMU_j) = \begin{cases} v_c\left(p_{cj}(1+\delta)\right), & if\ c\ is\ being\ maximized \\ v_c\left(p_{cj}(1-\delta)\right), & if\ c\ is\ being\ minimized \end{cases}$$

Hence, $v_c^L(DMU_j) \leq v_c(DMU_j) \leq v_c^U(DMU_j)$, for $c=\{1, \ldots ,q\}$.

The VBDEA allows to compute an optimistic efficiency measure and a pessimistic efficiency measure. Making the necessary adjustments to the formulations presented in Gouveia et al. (2013) in order to take into account ND factors, the optimistic efficiency measure $d_k^{opt^*}$ for DMU_k is computed by solving problem (3), and the pessimistic efficiency measure $d_k^{pes^*}$ for DMU_k is obtained by solving problem (4).

$$\min_{d_k,w} d_k^{opt}$$

$$s.t. \sum_{c=1}^{q} w_c v_c^L(DMU_j) - \sum_{c=1}^{q} w_c v_c^U(DMU_k) \leq d_k^{opt}, j = 1, \ldots, n; j \neq k \tag{3}$$

$$\sum_{c=1}^{q} w_c = 1, c \in D$$

$$w_c \geq 0, \forall c = 1, \ldots, q$$

$$w_c \leq 1, \forall c \in ND$$

$$\min_{d_k,w} d_k^{pes}$$

$$s.t. \sum_{c=1}^{q} w_c v_c^U(DMU_j) - \sum_{c=1}^{q} w_c v_c^L(DMU_k) \leq d_k^{pes}, j = 1, \ldots, n; j \neq k \quad (4)$$

$$\sum_{c=1}^{q} w_c = 1, c \in D$$

$$w_c \geq 0, \forall c = 1, \ldots, q$$

$$w_c \leq 1, \forall c \in ND$$

The optimal values of (3) and (4) allow to build a variation range of the efficiency of each MU_k: $\left[d_k^{opt^*}, d_k^{pes^*}\right]$. The DMU_k is robustly efficient (or robustly inefficient) if after the changes made in its factors it remains efficient (or inefficient), for the considered tolerance; otherwise, it is potentially efficient.

4. Data, criteria, and value functions

The Programme for International Student Assessment (PISA) is a three-year international study coordinated by the OECD aimed at evaluating education systems around the world, examining the skills and knowledge of 15-year-old students. Its results allow contrasting the educational systems in different countries, thus enabling the development of effective policy analysis in diverse contexts (OECD, 2017). Until 2018, since the first cycle in 2000, students from more than 80 countries have participated in the PISA assessment (INEVAL, 2018).

PISA-D uses the Educational Prosperity model (Willms, 2018) as a general analytical framework. It also takes into account the objectives of PISA-D (measurement of skills in the three areas of learning), lessons learned in past PISA cycles and other international studies, recommendations of research literature and priorities of participating countries.

PISA-D is an evaluation that was born as an initiative aimed at making PISA a more relevant proposal in the context of countries with small and medium-sized economies, for which it adapts the instruments and expands the spectrum of skills measurement and context questionnaires (OECD, 2018b).

The countries participating in PISA-D are low- and middle-income countries with higher poverty, illiteracy, and unemployment rates than OECD countries. The 7 countries participating in this edition belong to Latin America, Asia and Africa (INEVAL, 2018).

During October 2017, more than 6000 15-year-olds who were studying between the 8th Basic General Education and 1st Baccalaureate took a two-hour reading, maths and science test in Ecuador. Students belong to educational institutions chosen from a random sample throughout the country. The tests applied are not directly linked to Ecuador's school curriculum; rather, they are based on competences, and they are internationally comparable (INEVAL, 2018).

About 37,000 students completed the school-based assessment, representing one million students of 15 years of age (in grade 7 or higher) in schools in the seven participating countries: Cambodia, Ecuador, Guatemala, Honduras, Paraguay, Senegal, and Zambia (OECD, 2018c). In the case of Ecuador, 5,664 students participated, showing that it represents a population of 213,593, belonging to a sample of 173 schools from a universe of 4,448 educational institutions. We focus on PISA-D data for Ecuador, which contains information about a total of 159 public schools without missing data.

Next, we will further describe and justify the factors used in our efficiency assessment.

4.1. Factors used in the VBDEA assessment

In our study we have selected the factors (inputs and outputs) used in other studies dedicated to the evaluation of schools' efficiency resorting to PISA data (see e.g., Henriques & Marcenaro, 2021; Aparicio et al. (2018, 2019); Agasisti & Zoido, 2018; Agasisti, 2013). These are described below.

Economic, social, and cultural status. PISA computes the student's socioeconomic status using the PISA Economic, Social and Cultural Level Index (ESCS). It is derived from various variables related to the family context of students: parents' education, their profession, certain household possessions that indicate their material wealth, the number of books and other educational resources available at home. PISA's economic, social, and cultural level index is internationally comparable. The ESCS index also enables the identification of students and schools with a high socioeconomic index and a low socioeconomic index, according to international standards (OECD, 2018a; Tramonte & Willms, 2010). This factor is viewed as a non-discretionary criterion -being minimized- (following, e.g., Giménez et al., 2007; Thieme et al., 2012; Agasisti and Zoido (2018); Aparicio et al., 2018 and 2019) and it will be explicitly used since the performance of schools can be affected by the socioeconomic status of the intake of pupils (Dyson et al., 2001). Since this factor shows simultaneously both negative and positive values its value function will be similar to the value function of Kahneman and Tversky (1979).

Basic school infrastructure and levels of school resources (basicinfra). PISA-D asked school principals to report on the availability and status of basic infrastructure (ceiling, windows, doors, etc.) and services (drinking water, sewerage, bathrooms, electricity) at the school. The value of the index varies between 0 (indicating the lack of all basic infrastructure elements and services) and 10 (indicating that these elements are present and in good conditions) - see OECD (2018a). This factor is employed as a controllable criterion (being minimized).

Instructional resources (instres). Although from a certain point forward the quality of the facilities and the teaching resources stops making a difference in the results of the students, there are data-driven studies from the Latin American Education Quality Assessment Laboratory (LLECE), such as Murillo & Román (2011) and Douglas Willms & Somers (2001) that suggest that in low- and middle-income countries, school resources have significant effects, even after taking into account the socioeconomic characteristics of their students. The PISA-D questionnaire considers the availability of instructional resources and teachers' use of them. The instructional resource index ranges from 0 (indicating the lack of all physical facilities and resources required for teaching) to 10 (indicating that all these elements are present and in good conditions). Intermediate values indicate the availability of instructional resources for a variable grade (OECD, 2018a). This factor is considered as a controllable criterion (being minimized).

The number of students per teacher (stratio). According to Henriques & Marcenaro-Gutierrez (2020) students can be viewed as the "raw material" that must be processed through the teaching and learning processes. Therefore, we use the number of students per teacher considering that the size of the classes can have various effects on learning (Rivkin, Hanushek, & Kain, 2005; Tavana, et al., 2018). PISA-D and PISA 2015 asked school principals about the average size of instructional language teaching classes in the modal course (Spanish classes in 10^{th} Basic General Education or 1^{st} Baccalaureate) for 15-year-old students in the country. They also asked about the total number of teachers and students in their schools, from which the student-per-teacher ratio was calculated (INEVAL, 2018; OECD, 2015). Generally, in order to obtain a positive relationship between this indicator and the amount of resources invested, this indicator is transformed it into its inverse, i.e. the teacher-student ratio (see, e.g., Agasisti (2013), Agasisti & Zoido (2018) and Aparicio et al. (2018; 2019)). Hence, in our case rather than considering the teacher-student ratio as factor being minimized, we will consider the student-teacher ratio as a factor being maximized with a particular value function (see Section 4.2).

Learning outcomes. We have considered the mean scores of students attending the same school in the three most important competences, i.e., maths (meanmaths), reading (meanread) and science (meansci). We have simultaneously used these three competencies in order to avert one of the pitfalls of DEA (Dyson *et al*. 2001). These factors are usually used in scientific literature as a proxy of learning outcomes and are viewed as controllable criteria being maximized (see e.g., Agasisti & Zoido (2018); De Witte & López-Torres, 2017; Tavana et al., 2018; Aparicio et al., 2018; 2019; Henriques & Marcenaro, 2021).

As it can be seen in Table 1, the average scores in maths, reading and science competences obtained by 15-year-old students from schools in Ecuador are below the OECD average in all three areas (490 mathematics, 493 reading, 493 sciences). They are also below but closer to the average of the Latin American and Caribbean countries (8^{th}) that participated in PISA 2015 and PISA-D (INEVAL, 2018). In the case of ESCS more than half of the students evaluated by PISA in Ecuador are among 20% of the international population with low ESCS (OECD, 2016. p. 219). In addition, the student-to-teacher ratio in Ecuador is 22, below the Latin American and Caribbean average of 30, also below the OECD with an average of 26 students in each instructional language teaching class (OECD, 2016b). The availability of teaching staff may also vary due to the combined effect of population density in a particular area and the structure of the school offering in that same area. For example, rural schools in many countries are normally population-poor, have smaller classes and student ratios per teacher because schools require a minimum number of teachers, even if the number of students is low.

The average level of basic infrastructure for schools in Ecuador corresponds to an index value of 5,081 on the 10-point scale, while the average level of instructional resources for schools in Ecuador corresponds to an index value of 4.45 on the 10-point scale. Among the countries participating in PISA-D, these values correspond to one of the highest levels (OECD, 2018b).

Table 1. Descriptive statistics of the criteria used in the efficiency assessment of Ecuadorian schools

	meanmaths	meanread	meansci	ESCS	instres	basicinfra	stratio
Mean	377.49 (379)	408.90 (406)	399.26 (398)	-0.915	4.45	5.081	22.24 (30)
S.D.	46.89	52.55	43.57	0.768	0.75	1.58	6.92
Minimum	483.45	249.63	282.30	-3.149	2.93	2.853	1.00
Maximun	257.12	519.56	497.65	0.995	7.10	10.00	54.20
Count	173	173	173	173	173	173	173

Note: between brackets it is possible to see the mean values for Latin America and Caribbean

4.2. Value functions

As already mentioned in section 3.1, the VBDEA overcomes some issues of the Additive DEA model, but it also surpasses the problem of having negative or null data which is something that usually hampers the use of classic radial DEA models.

The DMs' preferences can be elicited in order to construct the partial value functions associated with each factor as it happens in Almeida and Dias (2012) and Gouveia et al. (2015, 2016, 2018).

The value functions used in the work are linear and non-linear. The factors to be minimized have nonlinear value functions (like instruction and basic school infrastructure resources) where the minimum performance value in the original scale is assigned the value 1 and the maximum performance value in the original scale is assigned the value 0 (see Figure 1). The non-discretionary factor (ESCS) also has a nonlinear value function, but this one is inspired in Prospect Theory. Using the Kahneman and Tversky (1979) value function we intend to incorporate the preferences of a hypothetical DM, that it is normally concave for positive values, viewed as gains and convex for negative values, viewed as losses - see Figure 2. Hence, the upper half part function of Figure 2 is used to illustrate positive value for ESCS, whereas the lower half part function of Figure 2 depicts its negative values. The factors to be maximized have linear (like the scores in maths, reading and science) and nonlinear value functions (the student-teacher ratio). In Figure 1 there is an example of a linear function, for the mean scores in reading, which is similar to the value functions considered for the other two competences. The nonlinear value function for the student-teacher ratio is convex with rapid growth until reaching the value of 30 and after that its value stabilizes, showing that up to 30 students per teacher (the Latin American and Caribbean average value for this factor), increasing a student is valued, but after that number one more student is not so well accepted, considering the impact that the size of classes can have on learning outcomes.

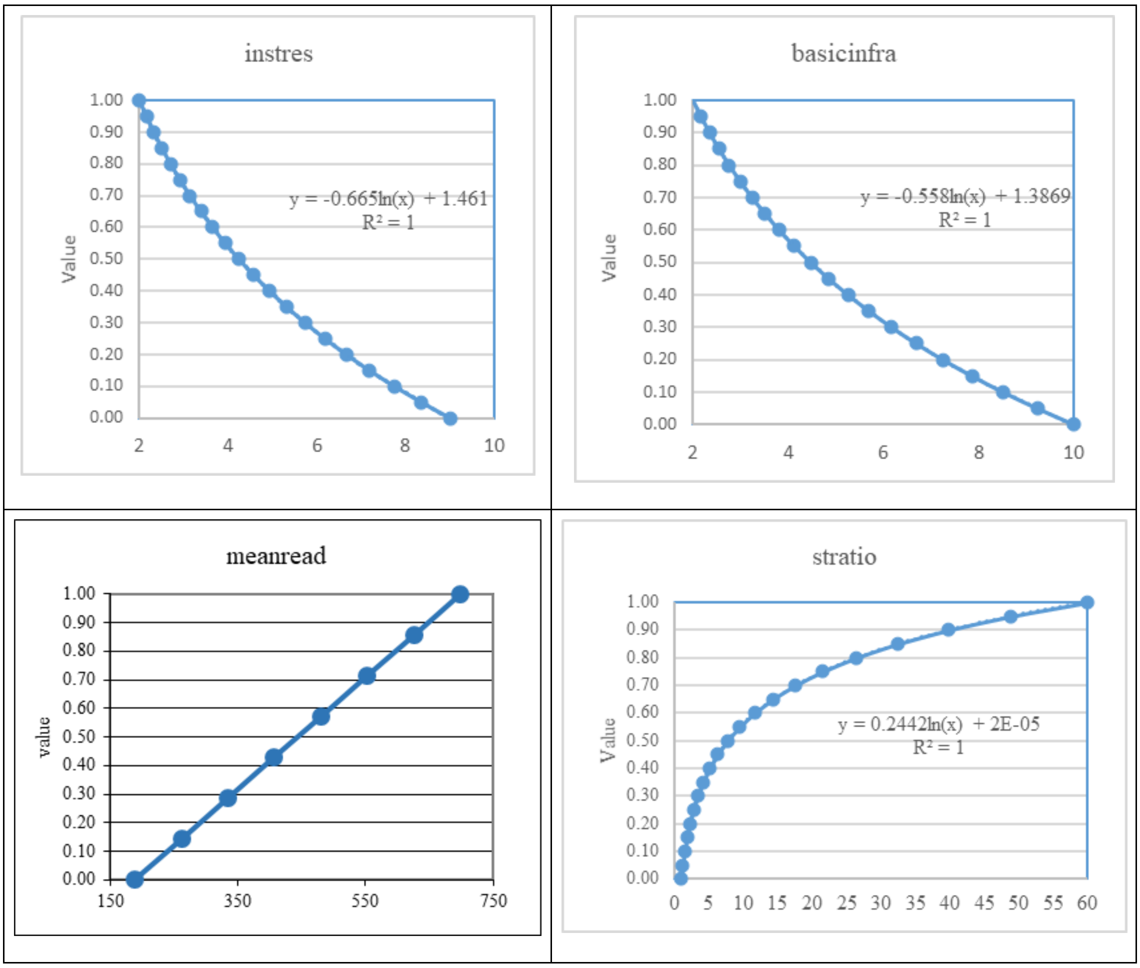

Figure 1. Illustration of some of the value functions.

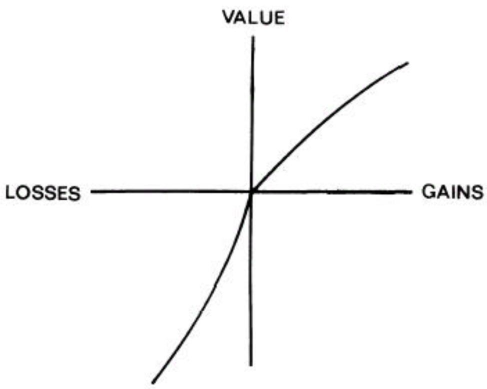

Figure 2. Hypothetical value function (Kahneman and Tversky (1979), p.279).

The value function for ESCS was constructed according to (5):

$$f_c\ (DMU_j) = \begin{cases} (p_{cj})^{\alpha}, & if\ \ p_{cj} \geq 0 \\ -\lambda(-p_{cj})^{\alpha}, & if\ \ p_{cj} < 0 \end{cases}, \qquad j = 1, \ldots, 159; c = \text{ESCS} \tag{5}$$

Tversky and Kahneman (1992) estimated α = 0.88 and λ = 2.25 from experimental data and those were the values for the parameters used herein. After that, we perform a normalization of the ESCS values through transformation (6), converting them into the range [0,1]. This transformation is typically used in MAVT problems.

$$v_c(DMU_j) = \begin{cases} \frac{f_c\ (DMU_j) - M_c^L}{M_c^U - M_c^L}, & if\ c\ is\ maximization\ criteria \\ \frac{M_c^U - f_c\ (DMU_j)}{M_c^U - M_c^L}, & if\ c\ is\ minimization\ criteria \end{cases}, j = 1, \dots, 159; \quad c = \text{ESCS} \tag{6}$$

Where the values $M_c^L < min\{f_c\ (DMU_j), j = 1, \dots, 159\}$ and $M_c^U > max\{f_c\ (DMU_j), j = 1, \dots, 159\}$, for ESCS.

5. Discussion of results

The efficiency results obtained in Table 2 indicate that in Ecuador there are only 28 schools that would meet the efficiency standards (efficiency score ≤ 0). The average efficiency of the entire sample reaches the score of 0.037; however, there are significant differences between the average values of schools with a variation in the level of efficiency ranging from -0.128 to 0.163 (see Table A1 from the Appendix). By contrasting these scores with the average maths, reading and science test results in each school analysed, it is possible to conclude that there is no consistent association between efficiency scores and the results obtained. For example, DMU 66 has the highest level of aggregate efficiency although its test results are quite modest; something similar also happens with other schools (see DMU 39, 122, 53, 68, 74, 82, 135, 153 and 87), which also gain a prominent place in the range of efficiency despite their poor results in either competence (see Table A1 from the Appendix). The contradiction of efficiency outcomes occurs when some schools which achieved fairly good results in maths, reading and science, are placed in the last position in terms of efficiency (e.g., DMUs 91 and 46), suggesting that these institutions are not adequately using their resources (see Table A1 from the Appendix). Despite this fact, Figure 3 shows a negative correlation between the scores in maths, reading and science and efficiency (-0.4354, -0.4592 and -0.4693, respectively), suggesting that these have a positive influence on efficiency, since the higher these scores, the higher the efficiency level attained (the lowest the score, the more efficient is the school), and a negative correlation between the number of students per teacher (-0.2215), also indicating that a high number of students per teacher leads to higher efficiency levels, while the level of school resources and the level of school infrastructure have a positive correlation (0.1050 and 0.0412, respectively), thus implying that a high level of resources means lower efficiency. The positive association between number of students per teacher and efficiency is not a common result in the previous literature; nevertheless, the association between class size and pupil performance is bedevilled with statistical problems[2] not least because in many education systems streaming or sorting takes place, providing smaller classes to the less able pupils. This confounds the estimation of the production function relating more teacher input to pupil outcomes (Dolton and Marcenaro, 2011). Additionally, this association could be qualitatively different for developed and developing countries and most of the previous literature focuses on the former; furthermore, higher students/teacher ratio could be related to higher teachers wages (to compensate for the higher student's burden), which could result in higher efficiency.

The information contained in Tables 2 and 3 allows us to conclude that efficient schools have higher average scores than inefficient schools in all the competencies considered. However, in contrast with inefficient schools they also show a higher variability of scores. In addition, efficient schools exceed average scores in all competences, surpassing national and Latin America and Caribbean mean values (INEVAL, 2018). It should be noted that according to the results of the competencies evaluated in PISA-D, the lowest average is mainly obtained in maths, whose value is below the Latin America and Caribbean average. These weaker results in maths are especially pronounced in Ecuador with a difference of more than 20 points between the performance of students in reading and science. Contrastingly, reading scores have better average scores in Ecuador. This behaviour differs from the results achieved in European countries, who achieve better outcomes in maths than in reading (Aparicio et al., 2018) using the results of PISA 2012, and those obtained with OECD (2016) data for PISA 2015.

Regarding the student-teacher relationship, the highest score is presented in efficient schools (26.34), while this relationship decreases in inefficient schools, with an average value of (21.36). Nevertheless, it should be noted that there is a wide variability in the results of this factor in both types of schools.

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[2] See, e.g., Lazear (2001) for a discussion on this issue.

This study identified 28 efficient schools; out of these, 22 operate in the urban area, or 78.6%, while only 6 belong to rural areas. In terms of school ownership, 8 are private in nature, representing 28.6% while the remaining are public.

The scores obtained in all competences by inefficient schools are lower than those obtained for the national average of PISA-D scores. In these schools the quality of educational resources is slightly higher than that of the national average; however, the level of infrastructures is relatively lower than the country's average. In what regards the average ECSC, the average score is much lower than the national average. Also, the values of the student-teacher relationship are slightly lower than the national average.

Overall, our findings indicate that regardless of the significant variation between schools, the position of the middle Ecuadorian school is closer to the average inefficient school.

Table 2. Descriptive statistics of the criteria of evaluation of efficient Ecuadorian schools

	meanmaths	**meanread**	**meansci**	**ESCS**	**instres**	**basicinfra**	**stratio**
Mean	403.58 (377.49)	437.45 (408.9)	425.75 (399.26)	-0.45 (-0.915)	4.53 (4.45)	5.35 (5.081)	26.34 (22,24)
S.D.	56.31	58.04	51.64	0.84	0.89	1.98	10.64
Minimum	257.12	305.42	314.58	-2.07	2.93	2.85	6.40
Maximun	483.45	519.56	497.65	0.79	6.48	10.00	54.20
Count	28	28	28	28	28	28	28

Note: between brackets it is possible to see the mean for Ecuador

Table 3. Descriptive statistics of the criteria of evaluation of inefficient Ecuadorian schools

	meanmaths	**meanread**	**meansci**	**ESCS**	**instres**	**basicinfra**	**stratio**
Mean	361.87 (377.49)	391.47 (408.9)	384.34 (399.26)	-1.18 (-0.915)	4.51 (4.45)	5.02 (5.081)	21.36 (22,24)
S.D.	41.97	48.53	38.74	0.71	0.73	1.49	5.51
Minimum	259.52	249.63	282.30	-3.15	3.24	3.03	1.00
Maximun	467.03	511.86	488.38	1.00	7.10	10.00	33.76
Count	131	131	131	131	131	131	131

Note: between brackets it is possible to see the mean for Ecuador

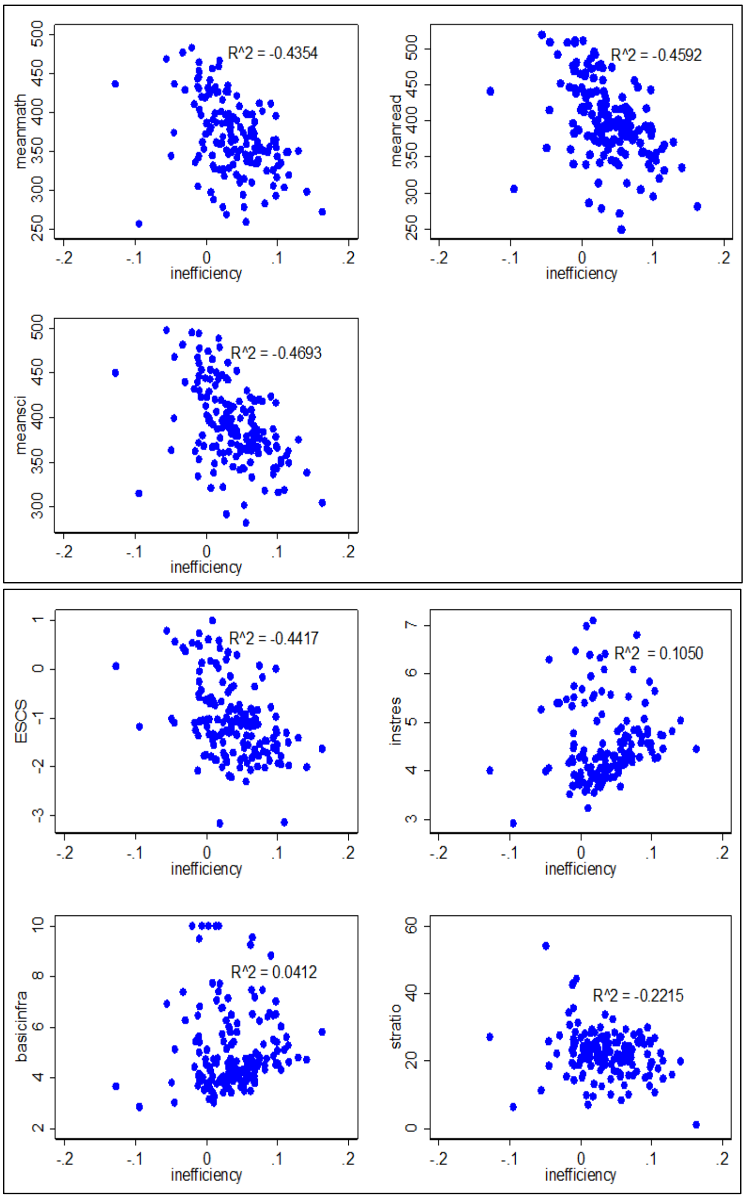


Figure 3. Efficiency score vs. evaluation criteria.

Figures 4 and 5 depict, in decreasing order of efficiency, the adjustments required on inputs and outputs for inefficient schools to become efficient. If we explore the projections obtained for each competence, we observe the existence of divergent values between these and the estimates of maths, reading and sciences, which become imperceptible when we only look at the average values analysed; for example, schools which operate with lower efficiency scores require substantially higher adjustments in maths, when compared to reading, and science, suggesting that they need to make a greater effort to improve the former outcomes, although the adjustments required in reading show greater variability.

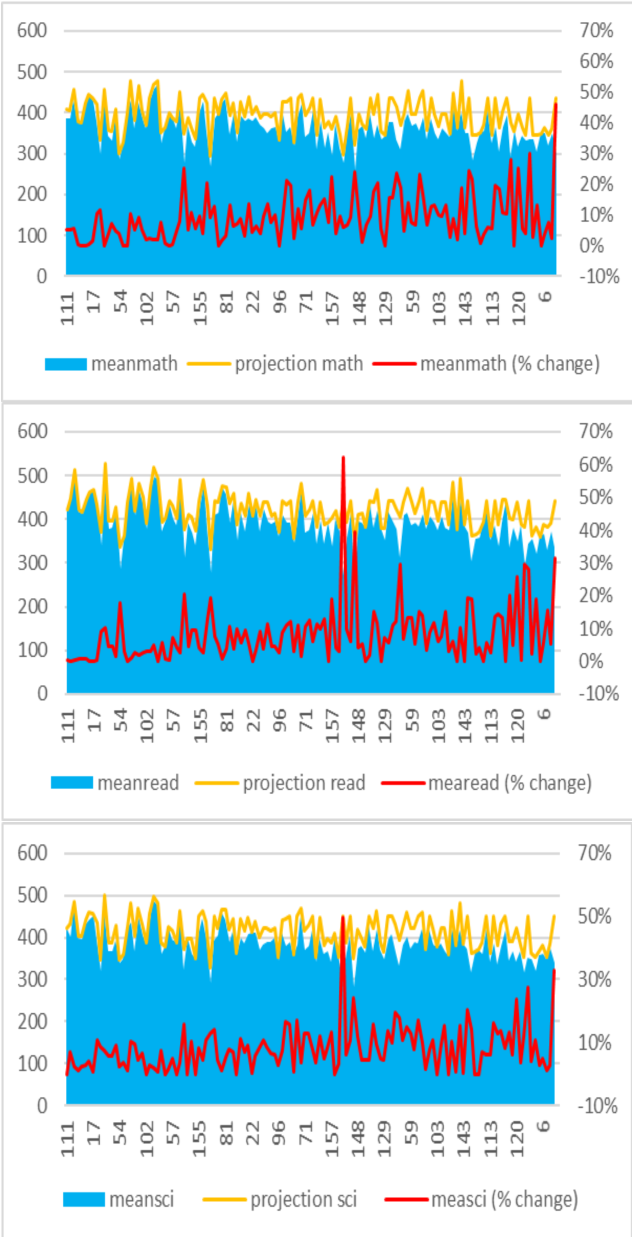
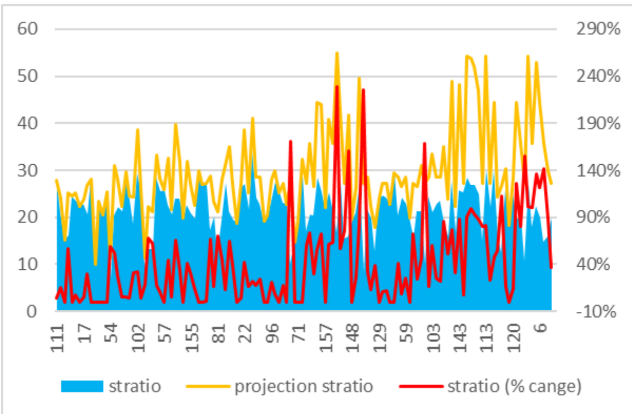


Figure 4. Real values vs projections (learning outcomes)



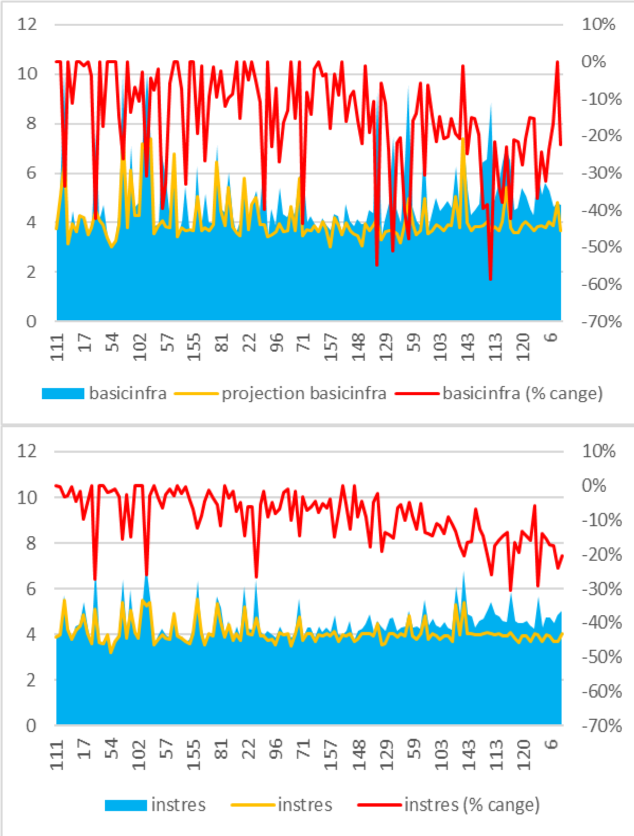


Figure 5. Real values vs projections (remaining criteria of evaluation)

Analogously to what was done previously, if we look at the projections for the remaining criteria of evaluation it is possible to perceive discrepancies between the projections and the ratio of students per teacher. In this case, they require increasing the number of students per teacher in schools with lower efficiency scores, meaning that these schools can reach better outcomes like their peers even with a higher number of students per teacher (and lower spending in teachers). In this case, it should be noted the fact that there are fewer students per teacher does not necessarily mean better results in the different competencies. Usually, teachers in the most disadvantaged schools are less qualified or experienced than those in the most advantaged schools (OECD, 2015). Hence, as already acknowledged in PISA, Ecuador should rather promote policies to enhance teacher quality even if this leads to bigger classes (OECD, 2015).

Regarding the values of the projection of the level of educational infrastructure and the level of the teaching resources of schools, these tell us that in most cases these factors could decrease, without further compromising the outcomes like in the schools viewed as benchmarks. In fact, these results suggest that these resources are not being properly exploited to obtain better academic results from students. We can also say that the investment made by the government of Ecuador from 2008 to 2016 in school infrastructures and endowment of materials for teaching (Benito Gil, 2016; Gil Gesto, 2017), did not allowed achieving the expected educational results. Despite the widely accepted idea that, if more resources are available, the better the performance of the students. Previous studies have shown that, once an adequate level of resources has been reached, this does not necessarily imply better learning outcomes (Hanushek, Kain, Markman, & Rivkin, 2003; Nanyonjo, 2007; OECD, 2016a; OECD, 2013; Wei, Clifton, & Roberts, 2012). This means that governments, schools and families should also focus on how educational resources are distributed and used, and which of them truly improve student learning abilities, as well as how much is invested in education.

5.1. Robustness assessment

One aspect that we are interested in analysing is whether the schools chosen as benchmarks are robust if the factors with intra-school variability suffer changes, such as in the case of the scores in maths, reading and science, and the ESCS index. Therefore, we have considered perturbations in these factors of 5%, 10% and 20%.

The results obtained in Table 4, show that there are seven schools (DMUs 66, 39, 53, 145, 3, 135 and 156) which remain surely efficient for all perturbations, while DMUs 114 and 145 belong to the top 5 DMUs more often viewed as benchmarks are only potentially efficient across all perturbations.

Moreover, although DMU 39 is the second DMU more frequently viewed as a reference of best practices, it achieves poor results in all competencies, despite using low levels of resources to produce them (see Appendix Table A1). DMU 66, which occupies the 1st place in the ranking of efficiency, and it is elected 62 times as a reference of best practices, achieves an overall balanced performance, both considering the competences scores and use of the different school resources.

Table 4. Specific characteristics of efficient Ecuadorian schools.

DMU	Efficiency score	N° Reference	Classif. (5%)	Classif. (10%)	Classif. (20%)
66	-0,1281	62	E++	E++	E++
39	-0,0952	33	E++	E++	E++
114	-0,0078	26	E+	E+	E+
53	-0,0493	21	E++	E++	E++
145	-0,0103	17	E+	E+	E+
68	-0,0455	13	E++	E++	E++
3	-0,0159	8	E++	E++	E++
55	-0,0104	7	E+	E+	E+

DMU	Efficiency score	N° Reference	Classif. (5%)	Classif. (10%)	Classif. (20%)
87	-0,0172	7	E+	E+	E+
122	-0,0560	7	E+	E+	E+
61	-0,0056	6	E+	E+	E+
74	-0,0447	5	E+	E+	E+
2	-0,0038	4	E+	E+	E+
43	-0,0101	4	E+	E+	E+
82	-0,0334	4	E+	E+	E+
46	-0,0095	3	E+	E+	E+
51	-0,0016	3	E+	E+	E+
67	-0,0098	3	E+	E+	E+
121	-0,0101	3	E+	E+	E+
135	-0,0299	3	E++	E++	E++
133	-0,0071	2	E+	E+	E+
153	-0,0201	1	E+	E+	E+
137	-0,0126	1	E+	E+	E+
156	-0,0117	1	E++	E++	E++
7	-0,0110	0	E++	E+	E+
91	-0,0101	0	E+	E+	E+
110	-0,0127	0	E+	E+	E+
117	-0,0011	0	E+	E+	E+

5.2. Weight restrictions

When the VBDEA methodology was introduced in Section 3, we have referred that the scale coefficients $w_1, \dots, w_q$ of the value functions are the weights that translate the possible values of trade-off between the different factors (Keeney & Raiffa, 1993). Each DMU can freely choose the weights associated with these functions or they can be restricted according to the preferences of the DMs. These weight restrictions can be incorporated into the DMU's efficiency assessment process.

Although there are no real DMs, we have built two possible scenarios that incorporate concerns inherent to the success in terms of the learning outcomes: a scenario revealing a DM more concerned with maths scores and another one focusing on reading scores. For that purpose, an order has been defined for the weights. For the first and second scenarios the order is respectively:

$w_{\mathbf{meanmath}} \geq w_{\mathbf{meanread}} \geq w_{\mathbf{meansci}} \geq w_{\mathbf{stratio}} \geq w_{\mathbf{instres}} \geq w_{\mathbf{basicinfra}}$,

$w_{\mathbf{meanread}} \geq w_{\mathbf{meanmath}} \geq w_{\mathbf{meansci}} \geq w_{\mathbf{stratio}} \geq w_{\mathbf{instres}} \geq w_{\mathbf{basicinfra}}$,

where $w_{\mathbf{meanmath}}$, $w_{\mathbf{meanread}}$, $w_{\mathbf{meansci}}$, $w_{\mathbf{stratio}}$, $w_{\mathbf{instres}}$ and $w_{\mathbf{basicinfra}}$ refer to the weights assigned to each factor, correspondingly.

The results depicted in Table 5 reveal the differences in the classification of efficient schools with and without restrictions, when we consider the first scenario. As it would be expected, the inclusion of additional restrictions decreases the number of schools classified as efficient. It should be noted that the scenario that gives more importance to the maths scores presents only 10 efficient schools out of a universe of 159, but if the greatest importance is given to reading, then there are 21 efficient schools. Then again, the results highlight the better performance of Ecuadorian schools in reading as opposed to maths.

Table 5. Efficiency with and without restrictions on the weights

DMU	Efficiency without restrict	Efficiency Scenario 1	Efficiency Scenario 2
2	-0.004		-0.0004
3	-0.016	-0.0008	-0.0159
7	-0.011		
39	-0.095	-0.0952	-0.0952
43	-0.010	-0.0049	-0.0080
46	-0.010		-0.0006
51	-0.002		-0.0016
53	-0.049		-0.0012
55	-0.010	-0.0007	-0.0015
61	-0.006		-0.0031
66	-0.128	-0.1275	-0.1275
67	-0.010		-0.0098
68	-0.046	-0.0054	-0.0114
74	-0.045		-0.0029
82	-0.033	-0.0104	-0.0058
87	-0.017		-0.0030
91	-0.010		
110	-0.013	-0.0079	
114	-0.008		-0.0048
117	-0.001		-0.0011
121	-0.010		-0.0049
122	-0.056	-0.0545	-0.0560
133	-0.007		
135	-0.030		
137	-0.013		
145	-0.010		-0.0020
153	-0.020	-0.0201	-0.0091
156	-0.012		

6. Conclusions

The efficiency evaluation of the educational sector is timely and relevant, concretely within the current COVID-19 pandemic, considering that public resources are scarce and compete with other public expenses (specially with those assigned to the health system).

Given the lack of studies which address the efficiency assessment of the global population of Ecuadorian schools through DEA, and the opportunity of using the latest

PISA-D data available, an empirical application is proposed which explores the use of the VBDA in the appraisal of Ecuadorian secondary schools' performance.

In this study we explicitly develop a new approach for incorporating non-discretionary factors in the VBDEA methodology. This latter methodology couples DEA with MCDA, thus encompassing in the efficiency assessment the main indicators (resources and outcomes) that might influence schools' efficiency. When contrasted with other DEA models, the VBDEA approach as several valuable characteristics since it enables translating the inputs and outputs typically used in traditional DEA models into value functions. This feature is particularly useful both for incorporation the preferences of DMs and for handling negative or null data. In this case, we have dealt with the Economic, Social and Cultural Level Index (ESCS), which presents both positive and negative data, by considering value functions inspired by the value function of Kahneman and Tversky (1979). Furthermore, this approach also allows addressing the robustness assessment of the efficiency scores reached, thus providing further insights into the sensitiveness of the results obtained in face of data perturbations. In this context, this technique can be relevant for evaluating changes in efficiency determined by factors with intra-school variability (e.g., those related to students, such as the scores in the distinct competences and the ESCS).

Overall, it can be ascertained that the average performance across all competences of efficient Ecuadorian schools is way above the average national school, but lower than the average in Latin American and Caribbean countries. Furthermore, we have established that, in general, schools showing lower efficiency levels usually need to make a bigger effort to improve maths scores when contrasting with the remaining competences. These results are reinforced when we include weights that either privilege maths or reading, thus leading to obtain 10 against 21 efficient schools, respectively, showing better performance of Ecuadorian schools in reading in contrast to maths.

Finally, schools more often viewed has benchmarks and classified as robustly efficient do not necessarily have a better performance in terms of learning outcomes.

In highlighting these points, we hope to have improved the knowledge of the methodology and the possibilities to apply it to international large-scale education achievement surveys, particularly to the extent that these international assessment programs (such as PISA-D) may influence education policy for the better and this methodology place more nuanced interpretations upon PISA-D results.

Despite the novelty of this paper, mainly by establishing a new way of handling non-discretionary data in VBDA, incorporating the preferences of a hypothetical DM and considering different scenarios through the introduction of constraints on the weights, it is not free of limitations. One of the limitations of this work is that it uses a hypothetical DM and not an actual one; additionally, it would be very useful to account with information about, for example, the teacher wages to the extent that it can be thought as a proxy for the quality of the education system. Last, but not least, ideally we would like to have panel data in order to evaluate the efficiency of the Ecuadorian educational system along the time.

Future research directions should include the possibility of conducting this sort of robustness evaluation in the comparison between schools from different countries, particularly those middle and low-income countries, which are the focus of the new features and enhancements contained in PISA-D.

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APPENDIX

Table 1A

Original factors vs efficiency scores DMU

DMU (n°)	School Id.	meanmaths	meanread	meansci	escs	instres	basicinfra	stratio	Efficiency Score
1	21800001	320.47	345.33	355.97	-1.33	3.86	4.64	22.75	0.042
2	21800002	353.15	387.46	368.11	-1.77	3.76	3.54	31.35	-0.004
3	21800003	336.09	360.39	362.35	-1.24	3.53	5.45	30.75	-0.016
4	21800004	272.24	281.70	304.45	-1.63	4.46	5.81	1.00	0.163
5	21800005	378.86	409.95	382.57	-0.87	4.36	6.53	20.31	0.064
6	21800006	349.89	366.65	362.19	-1.49	4.72	5.27	20.00	0.116
7	21800007	342.44	382.72	371.59	-0.51	4.18	5.65	43.00	-0.011
8	21800008	396.01	443.38	416.46	0.01	5.84	6.53	12.64	0.098
9	21800009	386.36	409.89	394.04	-0.99	4.07	4.03	26.88	0.028
10	21800010	388.31	413.38	419.81	-0.36	5.53	7.19	21.22	0.067
11	21800011	325.20	355.92	365.03	-1.47	4.58	4.74	26.94	0.085
12	21800012	459.85	496.00	488.38	0.60	7.10	10.00	9.51	0.018
13	21800014	315.21	343.96	361.98	-1.85	4.12	4.17	28.43	0.048
14	21800016	441.85	462.15	442.54	-0.70	4.43	4.27	22.30	0.005
15	21800017	416.46	475.89	447.67	-0.26	5.04	6.77	20.61	0.023
16	21800018	347.08	393.01	389.26	-1.27	3.89	4.42	19.35	0.031
17	21800019	428.94	466.96	453.54	0.17	5.41	4.26	22.73	0.005
18	21800020	412.14	456.46	420.16	0.08	6.08	6.25	15.80	0.074
19	21800021	335.49	344.87	352.89	-1.95	4.27	4.32	10.65	0.105
20	21800022	350.56	369.11	374.08	-1.46	4.78	4.31	25.21	0.082
21	21800023	359.91	398.73	377.40	-1.35	3.90	3.95	28.35	0.019
22	21800024	380.50	407.73	411.83	-1.08	4.27	3.92	27.14	0.034
23	21800025	352.72	391.44	379.94	-1.06	4.04	4.33	25.26	0.040
24	21800027	335.26	378.13	362.79	-1.37	4.15	4.55	22.77	0.063
25	21800029	376.22	419.05	399.83	-1.02	4.34	3.15	16.11	0.003
26	21800030	402.08	447.18	418.12	-0.16	6.80	7.47	16.89	0.079
27	21800031	387.26	405.44	417.86	-1.15	4.70	4.28	10.10	0.068
28	21800032	354.66	382.57	384.69	-1.73	4.24	3.89	15.71	0.067
29	21800033	303.98	320.72	318.84	-3.13	4.29	5.11	17.88	0.109
30	21800034	372.82	391.35	390.42	-1.08	4.33	4.05	19.92	0.067
31	21800035	426.81	459.40	442.69	0.04	5.50	7.40	25.00	0.017
32	21800036	423.80	439.56	428.86	-0.59	4.37	3.64	23.46	0.004
33	21800037	346.65	358.38	365.38	-0.92	4.13	4.75	27.12	0.055
34	21800038	319.60	330.76	348.99	-1.98	4.47	4.64	14.80	0.116
35	21800039	390.22	397.73	384.46	-1.01	4.08	4.32	10.03	0.042
36	21800040	293.24	334.73	343.96	-1.23	4.57	4.52	26.04	0.098
37	21800041	394.15	407.96	411.85	-0.35	4.37	5.43	27.60	0.038
38	21800042	362.89	422.51	382.54	-1.23	4.15	4.39	24.22	0.035
39	21800043	257.12	305.42	314.58	-1.17	2.93	2.85	6.40	-0.095

DMU (n°)	School Id.	meanmaths	meanread	meansci	escs	instres	basicinfra	stratio	Efficiency Score
40	21800044	310.58	313.16	333.09	-1.81	4.28	3.99	29.38	0.064
41	21800045	350.72	370.99	374.73	-1.41	4.82	4.81	15.90	0.129
42	21800046	456.15	479.57	465.30	1.00	6.98	7.74	9.93	0.008
43	21800047	445.69	468.72	461.74	-0.58	4.48	4.17	22.29	-0.010
44	21800048	259.52	249.63	282.30	-2.30	3.69	3.87	16.00	0.056
45	21800049	361.02	386.77	388.35	-2.00	3.85	4.02	22.58	0.022
46	21800050	452.39	508.02	477.28	0.48	5.51	6.81	18.81	-0.010
47	21800051	328.18	353.12	348.67	-1.84	3.75	3.25	20.39	0.012
48	21800052	389.68	429.00	412.89	-0.77	4.22	4.75	21.75	0.034
49	21800053	375.20	411.83	396.01	-1.33	3.77	4.45	24.43	0.004
50	21800054	467.03	492.15	478.67	0.42	5.57	7.73	13.24	0.019
51	21800055	418.86	465.31	443.47	-0.63	4.29	4.73	18.85	-0.002
52	21800056	390.83	420.97	392.05	-0.66	4.07	3.40	25.52	0.010
53	21800057	344.63	362.61	363.54	-1.02	4.00	3.81	54.20	-0.049
54	21800058	288.05	286.18	338.08	-1.54	3.24	3.03	7.11	0.010
55	21800059	453.97	471.59	460.53	-0.04	4.79	5.00	26.43	-0.010
56	21800060	298.14	339.52	321.03	-1.79	3.58	3.92	28.11	0.006
57	21800061	385.89	401.02	395.99	-1.28	3.95	5.71	25.80	0.022
58	21800062	344.91	378.36	366.81	-1.46	3.64	4.06	23.48	0.008
59	21800063	368.87	387.09	374.78	-1.13	4.28	4.64	22.89	0.066
60	21800064	336.39	379.66	370.27	-2.06	4.35	3.49	12.76	0.062
61	21800065	362.63	387.94	380.33	-1.05	3.91	4.02	44.38	-0.006
62	21800067	427.17	478.92	444.37	0.20	6.33	6.28	19.69	0.027
63	21800068	393.09	414.29	398.78	-1.30	4.34	3.57	19.38	0.032
64	21800069	317.96	341.95	351.41	-1.76	3.76	3.72	22.53	0.026
65	21800070	278.62	313.73	322.34	-1.49	3.92	3.42	24.05	0.023
66	21800071	436.47	441.07	449.78	0.07	4.02	3.66	27.15	-0.128
67	21800072	403.91	444.81	430.22	-0.04	3.93	5.41	24.28	-0.010
68	21800073	373.93	415.17	398.85	-1.10	4.06	3.03	25.81	-0.046
69	21800074	397.45	416.17	404.87	-1.26	4.06	3.96	17.26	0.028
70	21800075	380.78	432.09	394.07	-0.58	4.23	3.49	20.67	0.006
71	21800076	342.31	369.37	369.07	-1.34	3.87	6.16	19.10	0.043
72	21800078	370.18	419.15	422.33	-1.17	4.58	9.26	19.80	0.061
73	21800079	371.00	372.57	370.87	-0.37	6.41	5.30	33.76	0.035
74	21800080	436.36	509.21	467.94	0.57	6.29	5.13	18.61	-0.045
75	21800081	381.16	398.89	399.28	-0.87	4.32	3.64	20.47	0.048
76	21800082	432.76	486.51	436.19	0.12	6.40	10.00	21.18	0.013
77	21800083	399.08	439.52	420.14	-0.73	4.06	4.61	22.18	0.012
78	21800085	355.74	377.57	376.99	-1.52	4.85	4.78	27.74	0.075
79	21800086	354.77	379.52	368.34	-1.65	4.49	4.58	18.26	0.098
80	21800087	305.85	339.39	336.83	-1.60	4.58	6.48	30.00	0.094
81	21800088	434.46	456.78	442.00	-0.47	5.17	4.59	12.40	0.030
82	21800089	477.22	492.13	481.58	0.44	5.41	7.39	22.19	-0.033

DMU (n°)	School Id.	meanmaths	meanread	meansci	escs	instres	basicinfra	stratio	Efficiency Score
83	21800090	367.40	391.67	378.88	-1.15	4.23	3.94	20.74	0.056
84	21800091	364.46	395.77	398.44	-1.07	3.99	4.54	20.39	0.035
85	21800092	398.74	441.40	413.79	-0.86	4.57	6.02	27.29	0.031
86	21800093	421.49	474.28	452.25	0.30	5.57	5.81	14.61	0.043
87	21800094	411.20	446.65	431.59	-1.09	4.17	4.43	34.35	-0.017
88	21800095	339.54	375.01	359.48	-1.77	4.18	4.57	18.86	0.073
89	21800096	408.13	415.97	417.82	-0.73	4.27	4.27	17.01	0.047
90	21800097	268.88	278.31	291.76	-1.88	3.68	5.15	26.96	0.028
91	21800098	465.07	511.29	494.14	0.73	5.75	9.49	14.31	-0.010
92	21800099	426.60	473.24	461.37	0.35	5.65	7.14	20.13	0.030
93	21800100	432.22	511.86	474.26	0.62	5.70	10.00	15.17	0.002
94	21800101	362.30	409.01	368.37	-1.37	3.96	3.77	28.17	0.014
95	21800102	355.90	392.95	362.37	-1.86	5.08	6.56	24.95	0.089
96	21800104	333.39	360.26	344.75	-1.71	3.86	3.89	23.27	0.037
97	21800105	377.51	417.14	395.09	-0.80	4.68	4.81	24.55	0.062
98	21800106	348.94	360.75	357.25	-1.29	4.75	5.62	22.40	0.112
99	21800107	327.50	370.60	360.35	-1.71	3.69	5.45	19.86	0.024
100	21800108	348.82	357.55	371.03	-1.72	4.71	6.42	26.80	0.086
101	21800109	328.60	352.74	361.96	-2.18	3.78	4.21	21.23	0.031
102	21800111	360.93	378.20	387.18	-1.02	3.84	4.78	29.27	0.016
103	21800113	334.40	373.92	378.02	-2.00	4.28	4.48	21.00	0.071
104	21800114	343.94	386.81	366.66	-1.54	4.57	5.07	19.62	0.099
105	21800115	399.11	416.09	406.02	-1.04	4.60	4.04	15.48	0.056
106	21800116	351.58	380.61	394.55	-1.90	4.40	3.72	30.00	0.028
107	21800117	352.31	392.35	366.75	-1.15	4.29	3.89	25.40	0.049
108	21800118	374.28	401.70	409.36	-1.01	4.82	4.33	25.37	0.052
109	21800119	411.47	416.86	423.45	-0.77	5.41	8.84	15.09	0.091
110	21800121	443.74	396.33	439.70	-2.07	4.25	3.67	19.36	-0.013
111	21800122	387.07	418.80	423.05	-1.03	3.88	3.76	27.00	0.000
112	21800123	363.34	389.81	390.57	-2.21	4.13	3.43	19.08	0.035
113	21800124	325.99	353.66	342.88	-1.41	4.86	4.86	29.91	0.094
114	21800125	397.18	438.45	423.18	-0.42	3.92	3.91	28.57	-0.008
115	21800126	377.95	397.69	408.95	-1.11	4.74	7.47	24.14	0.063
116	21800127	362.92	406.98	386.07	-0.84	4.55	4.62	22.82	0.072
117	21800128	372.47	414.87	412.90	-1.75	3.72	4.55	19.55	-0.001
118	21800129	400.90	440.95	419.89	-0.66	4.25	6.75	25.47	0.021
119	21800130	338.01	380.51	366.15	-1.55	4.11	4.38	21.62	0.059
120	21800131	316.67	348.25	342.37	-1.29	4.51	5.41	25.13	0.099
121	21800132	431.23	477.37	446.61	-0.25	4.55	5.41	25.29	-0.010
122	21800133	468.66	519.56	497.65	0.79	5.26	6.93	11.30	-0.056
123	21800134	365.37	392.95	387.93	-0.82	4.05	4.21	23.08	0.041
124	21800135	364.41	387.67	386.94	-1.41	4.78	5.52	22.13	0.094
125	21800136	314.66	371.29	342.34	-1.60	4.00	4.25	21.91	0.053

DMU (n°)	School Id.	meanmaths	meanread	meansci	escs	instres	basicinfra	stratio	Efficiency Score
126	21800137	283.53	305.06	318.24	-2.02	4.29	4.49	28.50	0.082
127	21800138	279.04	271.64	301.63	-1.80	3.97	3.48	16.73	0.053
128	21800139	387.23	438.25	406.29	-1.85	4.08	4.58	18.64	0.014
129	21800140	345.30	353.58	349.64	-1.08	4.17	4.09	24.04	0.062
130	21800141	349.06	393.57	389.78	-1.15	3.98	6.50	22.92	0.035
131	21800142	334.70	377.47	367.30	-1.65	4.38	3.78	21.20	0.068
132	21800143	364.96	392.69	378.52	-0.97	4.55	7.02	15.78	0.097
133	21800144	420.00	481.82	453.51	0.14	6.48	10.00	25.43	-0.007
134	21800145	310.39	342.78	341.27	-2.02	3.87	3.94	20.56	0.047
135	21800146	429.40	452.13	439.61	0.38	5.41	6.26	27.66	-0.030
136	21800147	334.91	354.93	349.51	-1.78	5.65	6.04	26.84	0.105
137	21800149	433.20	476.57	467.11	0.52	5.34	6.47	23.36	-0.013
138	21800150	337.03	381.90	363.72	-1.03	4.44	3.99	27.19	0.056
139	21800151	426.38	472.67	450.58	0.12	5.95	7.07	23.50	0.014
140	21800152	332.26	379.51	367.36	-1.33	3.61	4.73	20.55	0.009
141	21800153	298.77	335.25	338.26	-2.00	5.05	4.72	19.88	0.141
142	21800154	350.30	392.60	382.01	-1.01	4.40	4.99	24.43	0.069
143	21800155	350.66	387.49	383.55	-1.68	4.86	5.32	25.75	0.080
144	21800156	385.57	446.44	402.71	-1.17	3.98	5.11	20.97	0.000
145	21800157	344.45	381.97	353.45	-1.07	3.69	3.87	35.71	-0.010
146	21800158	331.75	294.68	315.80	-1.93	4.39	4.54	19.76	0.101
147	21800159	378.73	370.75	387.50	-1.27	3.93	4.08	18.76	0.032
148	21800160	359.84	394.41	375.00	-1.35	4.15	4.14	19.59	0.056
149	21800161	351.20	381.07	367.21	-1.13	4.31	4.89	23.45	0.073
150	21800162	397.79	432.52	430.24	-1.92	4.89	4.52	8.33	0.057
151	21800163	326.59	372.97	360.28	-3.15	3.56	3.86	13.13	0.019
152	21800164	350.13	374.44	379.72	-1.04	4.32	4.03	32.37	0.045
153	21800166	483.45	508.94	495.17	0.54	5.48	10.00	15.38	-0.020
154	21800167	385.57	434.38	409.10	-0.13	6.08	5.81	26.17	0.033
155	21800168	397.50	423.38	414.90	-1.78	4.30	3.66	20.74	0.026
156	21800169	305.34	340.18	334.43	-1.36	3.71	4.07	42.66	-0.012
157	21800170	294.49	338.87	343.38	-1.51	4.08	3.67	22.00	0.052
158	21800171	397.73	416.11	400.98	-1.07	5.03	9.55	24.27	0.065
159	21800173	368.93	391.52	398.67	-1.09	3.93	4.07	23.90	0.023