

Technical efficiency of the districts and zones in intermediate education of Ecuador

Miguel Ruiz, Ph. D¹, Leonardo Estrada, Ph. D¹, Cristina Yoong, M.S.c¹, Vanessa Ormeño. Ec.²

¹Escuela Superior Politécnica del Litoral, Ecuador, miruiz@espol.edu.ec, mestrada@espol.edu.ec, cryoong@espol.du.ec

²Nanjing Agricultural University, China, vanessaormeno@hotmail.es

Abstract: *The objective of this paper is to analyze the efficiency in the administrative management of secondary education in Ecuador. First, A literature review was conducted to analyze the advantages and disadvantages of the methodology that has been previously applied in other investigations. For this study a data envelopment analysis (DEA) was applied in school districts as decision making unit (DMU). The pure technical efficiency (PTE) was estimated using three inputs (students, teachers, and budget) and three outputs (global index of approve “Ser Bachiller” test, retention rate and students approve test by subject) in 140 districts. The results suggest that in general the districts are efficient (PTE average > 0.5 in all models). Moreover, we found that the most efficient school districts are in zone 8 (Guayaquil, Samborondón, Durán) and zone 9 (Metropolitan District of Quito). Finally, sensitivity analysis suggests that the number of students in each school district (input 1) is not significant in the estimation of technical efficiency coefficients in the DEA model. These results may help to identify new strategies to increase the rate of student admission to universities.*

Keywords-- *inputs, outputs, technical efficiency, scale effect, development, zones, school districts.*

I. INTRODUCTION

In recent years, substantial changes have been made to the public administration system in Ecuador. The National Secretariat of Planning and Development (SENPLADES) divided the country into nine zones for better planning and control (see figure 1). Each zone is composed of districts. These are the main points of management and distribution of basic services throughout the country. In the case of education, the Ministry of Education is responsible for the distribution of the budget and the needs of public schools.

Reference [11] indicate that efficiency can be measured as the ratio between a company's performance observed at the output level, and its maximum possible level of output given the level of inputs. This implies that the production function of each company and the production possibilities frontier in a specific market must be known or estimated.

However, unlike private companies, there are some obstacles to measuring efficiency in public education. For instance, (1) Public educational institutions are not-for-profit

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companies, so there is no management measure, such as the level of profitability in the case of the private sector; (2) in the public sector it is often complicated to have information on production or price terms used and (3) there are many variables that can be considered inputs or outputs, so different approaches can be obtained.

The National Evaluation and Admission System (SNNA), created in 2011, oversees regulating admission quotas to public higher education institutions. The SNNA establishes a unified national system of enrollment, evaluation, and allocation of quotas according to the merit of each student, which considers the heterogeneity of the bachelor's degree and the requirements of university careers. In the same year, the National Higher Education Examination (ENES) was created, which assesses student knowledge and can be used to directly estimate an educational production function. During the first years of implementation of this test, the admission rate to higher education fell from 30.1% in 2011 to 26.6% in 2013.

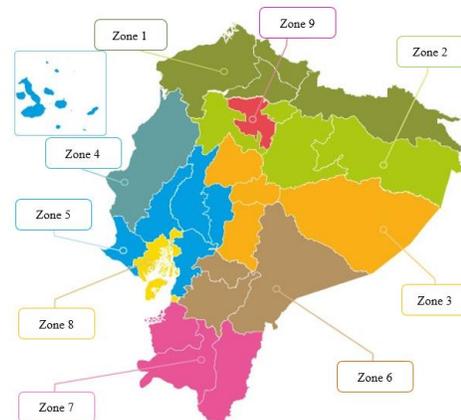


Figure 1: Geographic distribution Zone of Ecuador

According to the literature, some authors have used different methodologies to estimate the production function and analyze the efficiency of educational institutions. Reference [25] used a parametric estimation (OLS) to establish a stochastic production frontier and calculated the level of efficiency for universities in Brazil, based on some of its determinants [14]; [16A disadvantage of these models is that only one dependent variable is used. In the education sector, it is difficult to perform analyses with only one variable. An alternative that has been used in recent years is the data envelopment analysis (DEA) model. [12]; [13]; [2].

The DEA model allows the use of more than one variable to evaluate the management of educational institutions. It also allows estimating the relative efficiency of the decision-making unit (DMU), in our case school districts. Some of the most used inputs in the literature have been overhead costs, personnel costs, equipment costs, research income, faculty/student ratio, research, and non-research personnel of the schools to generate outputs such as graduate students, number of graduate research, number of publications, appointments, academic performance, among others. [1]; [9]; [3].

The paper aims, First, examine the pure technical efficiency of 140 school districts of educational institutions in Ecuador for the year 2015, applying the non-parametric method called data envelopment analysis (DEA). The second is to compare average efficiency in different areas. Finally, to provide empirical and consistent evidence for the design of redistributive and comparative policies that seek efficiency in public administration.

II. EDUCATIONAL ADMINISTRATION SYSTEM IN ECUADOR

To achieve "good living" it is necessary to transform the State. This governmental idea allowed the country to be divided into 9 zones with 140 districts and 1420 circuits. Each zone represents a group of districts and is formed by the provinces of Ecuador (see Table I). SENPLADES defines districts as the main units of administration and distribution of public services. In this study "scholar districts" will be considered as decision making units (DMU).

Each zone is composed of a different number of districts. For example, Zone 1 has 16 school districts, while Zone 2 has 8 school districts (see Table I). This distribution is used by the Ministry of Education to allocate the contributions to each school district.

The performance of secondary schools depends to a large extent on the way the school district manages and distributes inputs, and the totality of all this represents the level of efficiency of the respective zones.

TABLE I
TERRITORIAL COMPOSE OF THE NINE PLANIFICATION ZONES IN ECUADOR

Planification Zone	Provinces that compose	Number of school districts
Zone 1	Esmeralda, Imbabura, Carchi, Sucumbios.	16
Zone 2	Pichincha, Napo, Orellana.	8
Zone 3	Cotopaxi, Tungurahua, Chimborazo, Pastaza.	19
Zone 4	Manabí, Santo Domingo de los Tsáchilas.	15

Zone 5	Santa Elena, Guayas, Bolívar, Los Ríos, Galápagos.	25
Zone 6	Cañar, Azuay, Morona Santiago.	17
Zone 7	El Oro, Loja, Zamora Chinchipe.	19
Zone 8	Metropolitan district of Guayaquil.	12
Zone 9	Metropolitan district of Quito.	9

A. "Ser Bachiller" test and secondary education

In 2015, the "Ser Bachiller" test was created, which must be taken by high school seniors. In this test, the Secretariat of Higher Education, Science, Technology, and Innovation (SENESCYT) evaluates five areas of knowledge: Mathematics, Language, Science, Social and abstract knowledge. To approve the test, students must score more than 700 out of 1000 points in each subject area. The results of this test represent 30% of the graduation grade and 70% of the university selection grade.

The "Ser Bachiller" test classifies the results as "insufficient", "elementary", "satisfactory" and "excellent". As a requirement for high school graduation and to gain access to the public university system, the student must score at least at the "elementary" level. The student must meet this requirement to enroll a public university.

The purpose of the study is to analyze the efficiency of school districts comprised of public schools that are not-for-profit organizations, therefore we are faced with concerns about the evaluation and control of operational activities. For this purpose, data from the Ministry of Education of Ecuador corresponding to 2015 will be used. First, the methodology applied for the study and a brief introduction to its application in the educational sector will be described. Then the results will be analyzed and in the last section the most relevant conclusions will be indicated.

III. DATA ENVELOPMENT ANALYSIS

The Data Envelopment Analysis (DEA) methodology is used to calculate a company's efficiency in transforming inputs into outputs relative to its peer group. DEA is a linear programming technique that transforms inputs and outputs into a measure of efficiency. In this case, based on a sample, the most efficient school district is identified using the DEA and compared with its peers. The most efficient rate is 1 while the least efficient are between 0 and 1. Although DEA does not calculate an optimal efficient rate, it differentiates the least efficient district of all.

In the case of [7], assume constant return of scale (CRS), the measure of efficiency using CRS consists of two components: "pure" technical efficiency and scale efficiency. The authors [4] (BBC model) measures the efficiency using the variable returns to scale (VRS) version. The results indicate that the

estimators were defined as "pure" technical efficiency and "managerial efficiency". The relative efficiency of a district can be found using the DEA formulation. First, assume that there are D schools districts, each district produces N output variables and uses M inputs. Let y_{jk} and x_{ik} be the j^{th} output and the i^{th} input for the k^{th} school district, respectively.

$$\begin{aligned} i &= 1, 2, \dots, M \rightarrow \text{inputs in districts schools} \\ j &= 1, 2, \dots, N \rightarrow \text{outputs in districts schools} \\ k &= 1, 2, \dots, D \rightarrow \text{districts schools} \end{aligned}$$

The relative efficiency $\hat{\theta}_k$ of the k^{th} district is then defined as:

$$\max \hat{\theta}_k = \frac{\sum_{j=1}^N v_{jk} y_{jk}}{\sum_{i=1}^M u_{ik} x_{ik}} \quad \text{s.t.} \quad 0 \leq \frac{\sum_{j=1}^N v_{jk} y_{jk}}{\sum_{i=1}^M u_{ik} x_{ik}} \leq 1; \quad 0 \leq v_j, u_i \leq 1 \quad (1)$$

Where v_{jk} is the value on the j^{th} output of the k^{th} school district and u_{ik} is the value on the i^{th} input of the k^{th} school district. A school's efficiency score depends on these values. In the traditional basic efficiency measure, the values in the input and output variables must be consistent, i.e., $v_{jk} = \frac{1}{N}$ for all j and $u_{ik} = \frac{1}{M}$ for all i , for all school districts. DEA uses the values that maximize each school district's efficiency score under the same conditions, any school district can use the same set of values to evaluate its own efficiency ratio, if it is not greater than one.

The DEA model for a specific school district can be formulated as a fractional linear programming problem, which can be transformed into an equivalent linear form in which the input and output values of the school district are used as decision variables. This study uses 140 school districts, the Eq. (1) show the maximization of RE_k into the following equivalent LP problem:

$$\max \hat{\theta}_k = \sum_{j=1}^N v_{jk} y_{jk} \quad (2)$$

Subject to the constraints:

$$\begin{aligned} \sum_{i=1}^M u_{ik} x_{ik} &= 1; \quad \sum_{j=1}^N v_{jk} y_{jk} \leq \sum_{i=1}^M u_{ik} x_{ik} ; \\ 0 \leq v_j, u_i &\leq 1; \quad \sum_{i=1}^M u_{ik} = \sum_{j=1}^N v_{jk} \end{aligned} \quad (3)$$

Condition $\hat{\theta}_k = 1$ guarantees that the school district used as a base is efficient according to DEA, with respect to all other schools in the sample.

One advantage of this methodology is that we can estimate DEA efficiency with input and output orientations. Under CRS specification input and output orientations provide identical DEA estimates. When using VRS the estimation coefficient may differ between the orientations used. The constant returns to scale hypothesis are only accepted if the DMUs run at optimal size conditions, as there are some factors such as economic and operational constraints, that do not allow reaching the optimal size, so we use the BCC variable return to scale model.

IV. DEA IN EDUCATION

The DEA methodology in education is usually applied in efficiency studies at the university, college/institute, district, or city level. Some studies have applied DEA in secondary education and considered various levels of data aggregation to evaluate school efficiency.

According to the literature, the application of the DEA method using aggregated data has increased. For instance, [5], [8] and [24] are the main author who have contributed to the topic of efficiency in secondary institutions. These studies have used different approaches to explain efficiency.

In general, most studies have used as input the socioeconomic characteristics of the students and school; number of teachers and student; class size and teacher characteristics such as experience, level of education, etc. Regarding the output, many studies, have used variables related to standardized scores, statistics measures such as mean [20], median [5] or as in our case the percentage of students who exceed a certain value [6]; [17].

V. METHODOLOGY

This paper applies data envelopment analysis (DEA) to examine the efficiency of 140 Ecuadorian school districts. Variable returns to scale (VRS) were used assuming that there is a relationship between scale of operations and efficiency.

Table II shows the outputs and inputs used in each model. In the orientation or maximization model, outputs increase without increasing inputs. In the first section, the pure technical efficiency (PTE) of the 140 school districts of models 1 to 5 is analyzed. In addition, an efficiency matrix is provided to provide an overview of the efficiency of the school districts under analysis.

TABLE II
MODELS

Model	Inputs	Outputs
1	Budget, Teachers	Global Index
2	Budget, Teachers, and Students	Global Index
3	Budget, Teachers	Retention rate of 8th Basic Education
4	Budget, Teachers, and Students	Retention rate of 8th Basic Education
5	Budget, Teachers, and Students	Global Index and Retention rate of 8th Basic Education

The matrix is composed of four quadrants, in the first quadrant are the districts with an efficiency ratio above average, and an overall ratio (models 1-2) or retention rate (models 3-4) above average. In the second quadrant are districts with an above-average production level and a below-average efficiency score. The third quadrant is made up of districts with an efficiency score and a production level below average. Finally, in the fourth quadrant are the districts with an efficiency score above average and a production level below their average.

The second section corresponds to the analysis of the efficiency of the educational districts in terms of the percentage of students who passed the four subjects that make up the ENES test (Mathematics, Language, Science and Social Studies). The last section evaluates the efficiency of the country's nine planning zones. In this case it is considered that the zones are heterogeneous, therefore we use the average efficiency of the districts that make up each planning zone. In addition, since the districts are made up of different numbers of educational institutions, the models were estimated taking into account the returns to scale.

VI. THE DATA INPUTS AND OUTPUT SELECTION

The study used a dataset of 140 Ecuadorian school districts for 2015, obtained from various administrative datasets of the Ministry of Education. The input and output selection in the education sector is of great importance to obtain correct results.

During the specification of the DEA model, two important issues must be considered. The first is the importance of outputs and inputs in model specification, and the second is the initial measurement and specification of the input-output model. The literature indicates that there are two kinds of inputs: those that can be controlled by schools and those that cannot be controlled by schools or DMUs. Some researchers have included all inputs to calculate efficiency [10]; [15].

However, other studies adopt the two-stage procedure to analyze efficiency, this procedure assumes that the input variables of the second stage affect the efficiency with which outputs are produced from the inputs, while the one-stage procedure assumes that all inputs affect the output production process. In this study, the one stage procedure will be used. In the literature, the educational operating cost and the teaching staff are the most selected inputs for analyzing education efficiency [18];[19];[21];[22];[23].

In this case, by applying the DEA methodology to measure the performance of school districts in Ecuador, some categories of district measures were identified. These categories are inputs or resources used, performance measures, and district characteristics.

A. Inputs

The variables to be used as inputs and outputs was conditioned by the availability of data. The variables under study are made up of three inputs that can be grouped into: (1) the total budget of each school district, (2) the number of teachers per school district, and (3) the number of students per school district.

B. Outputs

As for the output variables, we have the following performance measures: (1) percentage of students scoring at or above the "elementary" level in each subject (mathematics, natural science, social science and grammar) (2) the sum of the percentage of students scoring at or above the "elementary" level in each subject by school district; (3) the retention rate of eighth graders.

VII. RESULTS AND ANALYSIS

This section presents the results of the efficiency evaluation using CRS or VRS, for which two procedures were performed. first, we obtained the efficiency coefficient with the VRS and CRS models. If $\theta_{VRS} = \theta_{CRS}$, it is assumed that there is no scale effect on the efficiency measure. So, we can use CRS, but if $\theta_{VRS} \neq \theta_{CRS}$, the CRS efficiency coefficient is not revealing the real efficiency of the district due to a scale effect. In our case, $\theta_{VRS} \neq \theta_{CRS}$, We will use the VRS to confirm the presence of variable returns to scale among school districts in Ecuador.

In VRS, technical efficiency (TE) scores of each model are decomposed into Pure Technical Efficiency (PTE) and Scale Effect (SE). In general, models 3, 4 and 5 show a higher average PTE coefficient than models 1 and 2 (see Table III). In other words, districts are more efficient at producing a higher retention rate than a proportion of students who pass the exam. Table III shows the five school districts for each

model. This allows us to know which are the best ranked models and whether they are affected by the inputs or outputs used in each model.

Figure 2 shows the efficiency histograms by model. The result show that the distribution in model 1 using output 2, are more spread out ($\sigma_1 = 0.14$) than model 3 ($\sigma_2 = 0.02$), using output 3. This is consistent even when input 3 is added in DEA models 2 and 4.

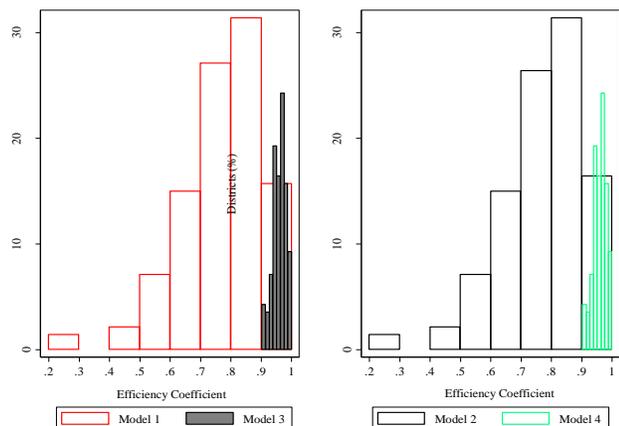


Figure 2: Histograms by model

Districts below the frontier have an efficiency score below 1 (or 100%) and, therefore, can improve their future performance. In model 1, districts 50 and 122 are on the relative efficiency frontier, followed by districts 19, 18 and 77, respectively.

The five lowest ranked districts are 40, 134, 133 and 100. When we add a variable (in this case, the total number of students enrolled in model 2), districts 50 and 122 are still on the efficient frontier, but also districts 18, 73 and 77. The least efficient districts are the same as in the previous model. In models 3 and 4, the five most efficient districts are 21, 103, 135, 73 and 86. The results suggest that the number of students in each district does not significantly affect the estimated coefficient of efficiency (PTE). In model 5 the five best and least efficient districts are a combination of the districts shown in the previous models.

On the other hand, a ratio analysis by efficiency matrix of the educational districts was performed. Figure 3 shows the distribution of efficiency levels in relation to their production levels in each of the estimated models. Each quadrant of the efficiency matrix represents a level established with respect to the level of production and the respective efficiency coefficient shown for each educational district. In model 1, 78 districts (55.71%) achieved an overall pass rate higher than 2.88.

In quadrant III, there are 54 districts (38.57%), which maintain a level of production below the average of all districts. In addition, the lack of efficiency in the utilization of teachers and budget is reflected in efficiency levels below 0.77.

TABLE III
TECHNICAL EFFICIENCY BY MODELS

Model 1 (0,771)						Model 2 (0,776)						Model 3 (0,961)					
Rank	Zone	District	SE	PTE	RTS	Rank	Zone	District	SE	PTE	RTS	Rank	Zone	District	SE	PTE	RTS
1	8	50	1	1	crs	1	1	50	1	1	crs	1	3	21	0,5864	1	drs
1	3	122	0,4702	1	drs	1	8	122	0,4749	1	drs	1	2	103	0,3976	1	drs
3	3	19	0,0951	0,9775	drs	1	7	18	0,5082	1	drs	1	2	135	1	1	crs
4	1	18	0,4615	0,9638	drs	1	7	73	0,9859	1	irs	4	7	73	0,4443	0,9987	drs
5	7	77	0,9042	0,9614	irs	1	3	77	1	1	crs	5	4	86	0,1269	0,9977	drs
136	1	40	0,3162	0,4570	irs	136	1	40	0,3162	0,4570	irs	136	9	107	0,1129	0,9092	irs
137	2	134	0,1469	0,4488	irs	137	2	134	0,1469	0,4488	irs	137	8	45	0,0914	0,9082	irs
138	2	133	0,3271	0,4439	irs	138	2	133	0,3390	0,4439	irs	138	6	98	0,3042	0,9072	irs
139	3	105	0,9083	0,2681	irs	139	3	105	0,9889	0,2770	irs	139	1	129	0,3211	0,9063	irs
140	6	100	0,7494	0,1989	irs	140	6	100	0,7494	0,1989	irs	140	3	104	0,0836	0,9022	irs
Model 4 (0,961)						Model 5 (0,962)											
Rank	Zone	District	SE	PTE	RTS	Rank	Zone	District	SE	PTE	RTS						
1	3	21	0,5864	1	drs	1	6	7	0,6815	1	drs						
1	7	103	0,4633	1	drs	1	1	18	0,5082	1	drs						
1	2	135	1	1	crs	1	3	21	0,7542	1	drs						
1	2	73	0,6549	1	drs	1	8	50	1	1	crs						
5	4	86	0,1269	0,9977	drs	1	7	73	1	1	crs						
136	9	107	0,1129	0,9092	irs	136	6	100	0,5756	0,9104	irs						
137	8	45	0,0914	0,9082	irs	137	8	45	0,1181	0,9082	irs						
138	6	98	0,3042	0,9072	irs	138	6	98	0,4524	0,9072	irs						
139	1	129	0,3211	0,9063	irs	139	1	129	0,4048	0,9063	irs						
140	3	104	0,0849	0,9022	irs	140	3	104	0,1387	0,9022	irs						

The other eight districts are divided into quadrants II (4.28%) and IV (1.43%).

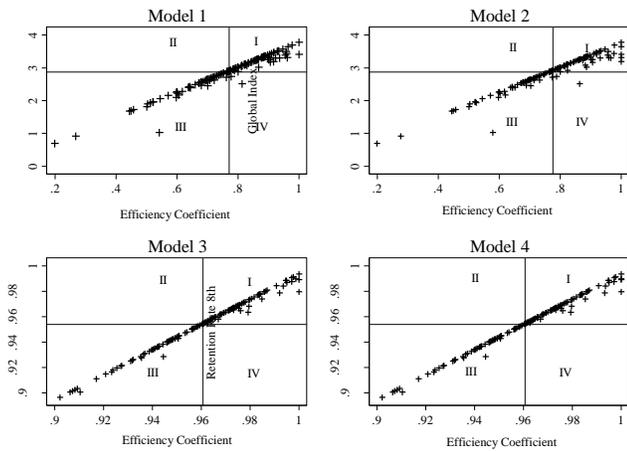


Figure 3: Efficiency Matrix by Model

In the second model, the number of students per district is considered as an additional data, the proportions, or the total number of districts per quadrant, do not present a considerable variation with respect to the first model. Considering the average production of the global index (2.8688) and the average efficiency coefficients (0.775). The results show that 75 districts (53.57%) are in quadrant number one, which shows that only 3 of the 78 districts observed in model 1, suffered a quadrant shift by including this input. On the other hand, in quadrant III, the 54 districts of the first model are maintained, the 11 missing districts are distributed between the quadrants II and IV.

In model 3, the proportion of districts in the first quadrant remains the same as in model 1. Although most districts have levels above the average student retention rate (95.40%) and efficiency coefficients above (0.9606). In the first analysis, it was established that by changing the production objective of the educational districts, the estimated efficiency levels for each district suffered a considerable variation.

However, the overall quadrant proportions show that, in this case, districts in the less efficient zone account for 42.85%, a higher proportion than that shown in models 1 and 2. However, the total efficiency range of the districts in model 3 is much lower than that observed in models 1 and 2. Model 4 shows the same proportions obtained in model 3.

In section two we analyze the efficiency of school districts by subject test, i.e., we use the percentage of students

scoring at least "elementary" in each subject (math, language, natural science, and social science). As in the first section, Table IV shows the estimated model for each subject, the 5 most efficient districts and the 5 least efficient districts. In this case, budget and number of teachers were used as inputs.

Table IV reports the PTE results by subject test, in mathematics districts 50, 122, 135, 10 and 19 are the most efficient, while districts 27, 50, 7, 33 and 46 occupy the top 5 positions in language.

Districts in Ecuador are more efficient at producing a higher proportion of students who pass or exceed "elementary" in Social Studies (0.835), while they are less efficient at producing students who pass mathematics (0.641) (see Figure 4).

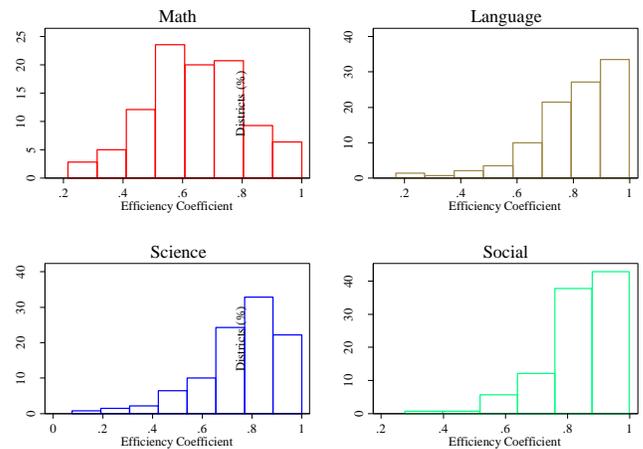


Figure 4: Efficiency Coefficient by subject

On the other hand, district 50, in zone 8, appears within the five most efficient districts in the 4 estimated models. In other words, for every dollar of budget per teacher that each district receives, the district's methodology and administrative management produces a higher proportion of students who pass the four subjects required for graduation from secondary education. Another of the districts that appears, in 3 of the 4 models, within the five most efficient is district 7 belonging to zone 6.

Likewise, districts 105 and 100, belonging to zones 3 and 6 respectively, are the least efficient in the production of this indicator. These districts rank among the bottom five in each of the four models. It is important to mention that district 100 belongs to the zone 6 as district 7.

TABLE IV
MODEL 1 BY SUBJECT

Inputs: Budget and Teachers											
Math (0,641)						Language (0,805)					
Rank	District	Zone	PTE	SE	RTS	Rank	District	Zone	PTE	SE	RTS
1	50	8	1	1	crs	1	27	3	1	0,527585	drs
1	122	3	1	0,5313	drs	1	50	8	1	1	crs
1	135	2	1	0,7377	irs	3	7	6	0,9836	0,6658	irs
4	10	5	0,9928	0,6751	drs	4	33	7	0,9805	0,3464	irs
5	19	3	0,9526	0,1074	drs	5	46	8	0,9775	0,1197	irs
136	132	1	0,3446	0,4329	irs	136	134	2	0,4176	0,1347	irs
137	91	4	0,3125	0,6363	irs	137	133	2	0,3910	0,2999	irs
138	40	1	0,2970	0,3573	irs	138	135	2	0,2963	1	crs
139	100	6	0,2667	0,7775	irs	139	105	3	0,1896	0,9020	irs
140	105	3	0,2151	0,9189	irs	140	100	6	0,1692	0,7327	irs
Science (0,754)						Social (0,835)					
Rank	District	Zone	PTE	SE	RTS	Rank	District	Zone	PTE	SE	RTS
1	50	8	1	1	crs	1	7	6	1	0,703354	drs
1	122	3	1	0,4851	drs	2	50	8	1	1	crs
3	17	1	0,9874	0,3204	drs	3	103	2	1	0,746237	drs
4	77	7	0,9803	0,9069	irs	4	122	3	1	0,474566	drs
5	7	6	0,9759	0,6956	drs	5	135	2	1	0,886098	irs
136	134	2	0,3914	0,1516	irs	136	40	1	0,5684	0,3191	irs
137	40	1	0,3891	0,3262	irs	137	61	5	0,5393	0,4717	irs
138	135	2	0,2717	1	crs	138	133	2	0,5307	0,3302	irs
139	105	3	0,1998	0,9109	irs	139	105	3	0,4561	0,9154	irs
140	100	6	0,0763	0,7563	irs	140	100	6	0,2768	0,7624	irs

Note: Average technical efficiency of the 140 districts by model in parenthesis; SE: Scale Effect; PTE: Pure Technical Efficiency; RTS: Returns of Scale

This shows that districts located in the same areas do not necessarily share high levels of technical efficiency and that there is potential for measures that can improve their productivity.

Table V shows the increase in the number of students in the districts as an additional input, and its influence on the estimation of the efficiency coefficients. The results suggest that this increase does not generate a meaningful change in the average level of efficiency in each of the subjects. The average efficiency per district increased by 0.007, 0.002, 0.004 and 0.002 in mathematics, language, science and social, respectively.

District 50 continues to be the most efficient. This district, belonging to zone 8, appears among the five most efficient in all four cases. In addition, districts 100 and 105 again appear among the 5 least efficient districts in the 4 models presented.

The results are consistent and robust with respect to the increase in the number of students as an input to the educational districts. Table VI shows the efficiency of the planning area according to model 1 and model 2, while Table VII presents the results for models 3 and 4.

To obtain a zonal efficiency indicator, the average level of the estimated coefficient for the districts that make up each of the country's nine zones was taken as a reference. In model 1, zone 9, composed of 9 districts located within the metropolitan district of Quito, presents the highest average 0.8651 (see Table VI).

In this area, eight school districts (88.89%) operated with increasing returns to scale (IRS) or economies of scale and one district (11.11%) with decreasing returns to scale (DRS) or diseconomies of scale. This means that school districts operating with DRS have grown beyond their most productive scale size and might consider reducing their number to improve their optimal size.

TABLE V
MODEL 2 BY SUBJECT

Inputs: Budget, Teachers, and Students											
Math (0,648)						Language (0,807)					
Rank	District	Zone	PTE	SE	RTS	Rank	District	Zone	PTE	SE	RTS
1	10	5	1	0,7440	drs	1	27	3	1	0,5346	drs
1	50	8	1	1	crs	1	50	8	1	1	crs
1	77	7	1	1	crs	1	73	7	1	1	crs
1	122	3	1	1	crs	1	77	7	1	1	crs
1	135	2	1	0,8056	irs	1	106	9	1	0,9905	irs
136	132	1	0,3446	0,4329	irs	136	134	2	0,4176	0,1347	irs
137	91	4	0,3125	0,6363	irs	137	133	2	0,3910	0,3116	irs
138	40	1	0,2970	0,3573	irs	138	135	2	0,3223	0,9923	irs
139	100	6	0,2667	0,7775	irs	139	105	3	0,1977	0,9918	irs
140	105	3	0,2337	0,9910	irs	140	100	6	0,1692	0,7327	irs
Science (0,758)						Social (0,837)					
Rank	District	Zone	PTE	SE	RTS	Rank	District	Zone	PTE	SE	RTS
1	18	1	1	0,5188	drs	1	7	6	1	0,7034	drs
1	50	8	1	1	crs	1	50	8	1	1	crs
1	77	7	1	1	crs	1	73	7	1	1	crs
1	122	3	1	0,4892	drs	1	77	7	1	1	crs
2	17	1	0,9874	0,3489	drs	1	103	2	1	0,8086	drs
136	134	2	0,3914	0,1516	irs	136	40	1	0,5684	0,3191	irs
137	40	1	0,3891	0,3262	irs	137	61	5	0,5393	0,4717	irs
138	135	2	0,2873	1	crs	138	133	2	0,5307	0,3402	irs
139	105	3	0,2032	0,9891	irs	139	105	3	0,4578	0,9900	irs
140	100	6	0,0763	0,7563	irs	140	100	6	0,2768	0,7624	irs

Note: Average technical efficiency of the 140 districts by model in parenthesis; SE: Scale Effect; PTE: Pure Technical Efficiency; RTS: Returns of Scale

On the other hand, school districts under IRS should consider increasing their size. In a situation of economies of scale, an output variation of 1% translates into an input variation of less than 1%. Therefore, an increase in production translates into a reduction in average input consumption.

Zone 2 has the lowest average efficiency level (0.6482). This zone, composed of the provinces of Pichincha (not including the city of Quito), Napo and Orellana, has 7 districts (87.5%) operating in SRI, and 1 operating in SDDR. The other zones and their respective positions in the ranking can be seen in Table VII. The model shows the results of the zonal indicators when the total number of students is added as an input in the model.

In addition, zone 9 continues to show the highest average efficiency per district, 0.8651. In fact, the average is the same as in the previous model.

This reinforces the idea that an increase in one input, particularly the number of students per district, does not generate a significant effect on the calculation of the technical efficiency ratio.

In models 3 and 4, efficiency was measured using the basic education retention rate as output, the results are shown in Table VII. Considering the retention rate as output, zone 4 is the most efficient (0.9769), followed by zones 2 and 3. The least efficient zone is zone 8, with a score of 0.9487. The efficiency range is the same in model 4, also the IRS of 100% is maintained for zones 9 and 8.

TABLE VI
MODEL 1 AND 2, RANK BY ZONE

Model 1					
Zone	TE	PTE	SE	IRS	DRS
9	0,1804	0,8651	0,2141	89%	11%
8	0,2496	0,8321	0,2800	92%	0%
7	0,3273	0,8283	0,3953	89%	11%
3	0,2941	0,8272	0,3705	79%	21%
5	0,2540	0,7532	0,3304	96%	4%
6	0,3116	0,7460	0,4403	94%	6%
1	0,2139	0,7177	0,3077	81%	19%
4	0,1508	0,7032	0,2293	100%	0%
2	0,2467	0,6482	0,3691	88%	0%
Model 2					
Zone	TE	PTE	SE	IRS	DRS
9	0,1846	0,8707	0,2127	89%	11%
7	0,3887	0,8460	0,4526	74%	21%
8	0,2496	0,8321	0,2800	92%	0%
3	0,3056	0,8295	0,3854	74%	26%
5	0,2604	0,7546	0,3363	96%	4%
6	0,3230	0,7485	0,4535	94%	6%
1	0,2235	0,7208	0,3172	81%	19%
4	0,1548	0,7032	0,2349	100%	0%
2	0,2634	0,6565	0,3804	88%	0%

TABLE VII
MODEL 3 AND 4, RANK BY ZONE

Model 3					
Zone	TE	PTE	SE	IRS	DRS
4	0,1588	0,9769	0,1631	87%	13%
2	0,2778	0,9760	0,2811	75%	13%
3	0,2506	0,9675	0,2566	84%	16%
7	0,2234	0,9633	0,2304	89%	11%
1	0,1991	0,9587	0,2085	94%	6%
6	0,2880	0,9571	0,3007	82%	18%
5	0,2171	0,9518	0,2283	96%	4%
9	0,1504	0,9500	0,1561	100%	0%
8	0,1957	0,9487	0,2062	100%	0%
Model 4					
Zone	TE	PTE	SE	IRS	DRS
4	0,1588	0,9769	0,1631	87%	13%
2	0,2869	0,9760	0,2902	75%	13%
3	0,2554	0,9675	0,2616	84%	16%
7	0,2599	0,9635	0,2676	89%	11%
1	0,2033	0,9587	0,2126	94%	6%
6	0,2880	0,9571	0,3007	82%	18%
5	0,2187	0,9518	0,2300	96%	4%
9	0,1504	0,9500	0,1560	100%	0%
8	0,1957	0,9487	0,2062	100%	0%

VIII. CONCLUSION

This paper shows an estimation of the management of public resources in the intermediate education service. In this case, we focus in 140 districts and 8 administration zones of Ecuador in 2015.

We used three specific variables as school district inputs, and two indicators as resource management outcomes. Using a non-parametric model (DEA) we calculated a technical efficiency indicator for each of the 140 school districts. Results show that the school districts are efficient in the "production" of the percentage of students who pass the "Ser

Bachiller" test (output 2) and student retention rates (output 3). However, public policy on education should reduce the efficiency gap between school districts. In this context, the results suggest that policies should be designed based on the percentage of students who pass the "Ser Bachiller" test. In other words, there is greater scope for policy action in indicator 2 with respect to indicator 3.

When each subject that makes up the "Ser Bachiller" test is evaluated independently, the results show that school districts are less efficient in mathematics and more efficient in social studies. In addition, this model presents a high variance, which means that there are districts, such as 50 (Tarqui - Guayaquil), whose percentage of students who pass the mathematics part of the exam is higher or equal to 1. On the other hand, there are districts that have very low coefficients, such as 105 (Araujo - Pastaza) with a pass rate of 0.22.

On the other hand, social is the subject in which districts are most efficient, i.e., for every teacher and every dollar of inputs that each district has, these inputs generate a higher proportion of students who pass this subject. However, we observe that a low proportion of students passing mathematics directly affects the probability of graduation and access to a prestigious university in each of the 140 districts. This is evidence of the weakness of educational and administrative institutions in teaching a subject that is fundamental for the professional development of young people.

Finally, it was found that the number of students enrolled in the institutions belonging to each district does not generate a relevant change in the estimation of efficiency levels. In other words, this variable has a non-significant effect on the calculation of district efficiency indicators. Regardless of the outputs analyzed, in this case, the overall index and the retention rate. It is recommended to identify the reason why the students do not achieve the required level in the evaluated subjects. In this way, policies and strategies can be developed to improve efficiency and increase university entrance rates.

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