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Measuring the impact of Socio-Economic Factors on school's Technical Efficiency

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ABSTRACT

This paper investigates and evaluates the effectiveness and the Technical Efficiency of secondary education units in the region of Western Macedonia in Greece. Using Data Envelopment Analysis (DEA) at a first stage analysis school efficiency is measured in schools where multiple inputs produce multiple outputs. In this study the inputs chosen are: the teacher student ratio, the staff student ratio and the computer student ratio of each educational unit. The output (student performance) refers to the student's achievement in the national exams during the school year of 2015 – 16. In the second stage analysis, efficiency scores from the first stage analysis, were explained in a regression with the environmental variables as independent variables. The independent variables chosen were divided in two categories: the variables from the direct school environment (school size, teacher's experience, teacher's qualifications and per student expenses) and variables from the wider school environment in (GDP per capita, unemployment rate and educational level of each school's area). DEA showed that 4 out of the 29 educational units were characterized as technical efficient becoming benchmarks for all the others with lower efficiency. In the second stage, regression analysis shows that teachers' experience significantly affects school efficiency while teacher's qualifications, school size and per student expenses do not affect school efficiency. Concerning the variables from the wider social environment, GDP per capita, unemployment rate and educational level in each school's area didn't show a statistically significant effect on the technical efficiency of the educational units.

Keywords: Technical Efficiency, School Effectiveness, Data Envelopment Analysis

INTRODUCTION

Scientific research to assess efficiency has its roots in the study of Charnes et al. (1978), who in their initial study approached the notion of Decision Making Units (DMUs) with the non-parametric Data Envelopment Analysis (DEA). Since then, for the next forty years to date, there has been rapid and continuous growth in the field. As a result, a considerable amount of published research has appeared, with a significant portion focused on DEA applications of efficiency and productivity in both public and private sector activities (Emrouznejad, Parker, & Tavares, 2008). The purpose of such scientific articles is to assess the efficiency of educational units and organizations in order to identify the factors that influence it while also providing particularly useful information for decision-makers related to educational policy. Furthermore, when the research takes place in countries where the school education system is public (like it is in Greece), important information on input and output prices are usually missing. Consequently, the measurement of efficiency in education is a complicated and controversial process, while in some cases there is no clear consensus on what the 'real' outputs are and how they should be measured, a problem that also occurs for the schooling inputs. In addition, some of the school inputs are not controllable by schooling institutions even though their influence on outputs is evident (Kirjavainen, 2009). Despite these difficulties, what emerges from the literature review (Sutherland, Price, Joumard, & Nicq, 2007), is that the basic types of factors that can affect student performance and therefore the efficiency of a school are two: The first type refers to "direct" inputs, which are under the supervision of the school system and the second type refers to the so-called "indirect" or "environmental" inputs. The measurement of efficiency is a measure adopted more and more often in various sectors, since it is large in scope. Banks and generally businesses, hospitals, schools and universities, are few examples of those who estimate their efficiency level. Concerning the public sector, the fact that the outputs are amorphous and intangible in many respects it makes it difficult to define a way to measure and evaluate the goods that are produced and offered to the market for free, which means that the prices of outputs are not determined by market forces. As economic efficiency cannot be directly measured, there is a need for a technique to proxy an efficiency frontier which would allow relatively accurate benchmarking. Economic theory recognizes several efficiency concepts like technical efficiency, cost efficiency, allocative or productive efficiency. The concept of technical efficiency is determined as the ratio of observed to maximum potential outputs obtainable from the given inputs or as the ratio of minimum potential to observed inputs required to produce to give outputs (Kirjavainen, 2009). In this study, technical efficiency of the school units is measured and the school unit is viewed as maximizing its outputs with the given inputs. The method used is the Data Envelopment Analysis (DEA), a non parametric approach described analytical below.

DATA ENVELOPMENT ANALYSIS

The methodology of DEA was developed based on the model of Charnes, Cooper & Rhodes (Charnes, Cooper, & Rhodes, 1978) and (Charnes, Cooper, & Rhodes, 1979), known in the literature as a model for CCR, from the initials of the authors. Charnes, in his study, describe the method of DEA as a mathematical programming model which is applied to empirical data and provides a new way of obtaining empirical estimates of relations, such as production functions, which are the cornerstones of modern finance. By transforming a system of nonlinear equations, which are particularly difficult to assess in practice, into a system of linear equations, Charnes, actually developed the first non-parametric model of DEA. A feature of the DEA method is that, unlike other methods, it doesn't require the determination of the production function. In this method, the total production capacity is determined through a process of linear integration of the observed input - output combinations for each DMU. This creates an empirical best practice frontier which is indicated as empirical production function and indicates a point of comparison and evaluation for the measurement of the efficiency of each DMU. The DMUs that are comparatively more efficient and belong on the frontier, become benchmarks for the rest DMUs, whose lack in efficiency is determined by their distance from this frontier. So the level of efficiency of a productive activity indicates the deviation (or non) of the observed production activity of a DMU by the activities of the better or best DMUs in the sample. At this point, it is necessary to be mentioned, that the DEA method assumes that at least one DMU is efficient. The DMUs with efficiency lower of the unit are inefficient, while the rest DMUs are considered as efficient simply because no other unit in the sample is more efficient than them. It is obvious that this does not mean that there is no possibility of achieving greater efficiency than it has under this rated level [34]. The reason is that the DEA method calculates the related efficiencies of DMUs and not their absolute values.

CCR and BCC models: The method DEA has developed considerably with the model of Banker, Charnes & Cooper [35] which is known as BCC model. It is a model with Variable Returns to

Scale VRS in contrast to the CCR model which is referred to the case of Constant Returns to Scale (CRS) and measures only efficiency of units and not the performance scale. This model is the one which is now widely used and assumes the existence of constant returns to scale (CRS DEA), where the sample units are operating at the optimum scale of production, leads to measurements of efficiency which does not take into account the effect caused by the production scale and which affects the level of the measured technical efficiency. The VRS DEA model, however, allows the calculation of efficiency, without the impact caused by the level of scale efficiency. With the VRS DEA model of a convex curve is constructed which is the result from the intersection of surface and embedding the data in a more compact group that follows the curve constructed on the assumption of constant returns to scale (CRS DEA model). Thus, the VRS model leads to a measurement of the level of efficiency, which is greater than or equal to those obtained by using the CRS model. Let in a DEA model, Xi be a vector of inputs and Yi a vector of outputs for the school i (i =1,...,N). Suppose X_0 and Y_0 are, respectively, the inputs and outputs of school 0 whose efficiency level is supposed to be examined. The measurement of efficiency for school 0 may be defined as follows:

$$Min\ \eta_0 \quad (1)$$

s.t.

$$\sum_{i=1}^{n} \theta_i Y_{ij} \geq Y_{0j} \qquad \forall\ j = 1,\dots,s \quad (2)$$

$$\sum_{i=1}^{n} \theta_i X_{ik} \leq \eta_0 X_{0k} \qquad \forall\ k = 1,\dots,m \quad (3)$$

$$\sum_{i=1}^{n} \theta_i = 1 \quad (4)$$

Where η_0 represents the efficiency level of school 0 and θ_i the weight given by the school i in order to dominate school 0 , j represents the outputs and k represents the inputs. Optimal η_0 cannot be greater than 1. If the score of school 0 is equal to 1 (η_0 = 1) then the school is defined as efficient whereas if it is less than 1 (η_0 < 1) the school is inefficient. In order to illustrate the above in graph form, an example composed of four schools (A, B, Γ and Δ) is now considered in which only one input (X) is used so that only one output (Y) is produced. Figure 1 represents the two dimensions of a plane on which the four schools are positioned.

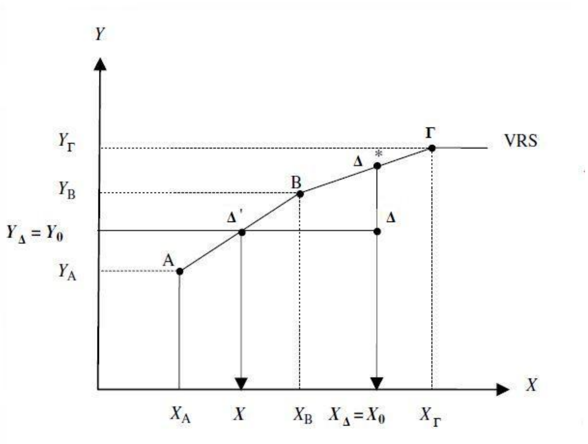

Figure 1. The DEA frontier

Schools, A, B, and Γ are efficient as they are situated on the frontier. On the other hand, school Δ is inefficient. The level of inefficiency can be measured (graphically) in two ways: either as the vertical distance between point Δ and Δ* (output oriented) or the horizontal distance between point Δ and Δ' (input oriented). The output-oriented measurements indicate the amount by which the outputs must be proportionally increased in order to reach the frontier while keeping inputs constant. The input-oriented measurements indicate the amount by which inputs could be proportionally reduced while keeping output quantities constant.

If it is considered that the aim of school headmasters is to obtain the best results possible sing the resources available (over which they exercise little or no control), the output-oriented version is appropriate (Mancebón & Bandrés, 1999). On the other hand, if the goal is that schools minimise the use of inputs while keeping their output level constant, then an input-oriented model is better (Kirjavainen & Loikkanen, 1998). In this chapter, we share the view that because of difficult budgetary context, educational policies are aimed at improving the use of resources (Diagne, 2006). The results are therefore input oriented, that is to say, a school is not efficient if an input can be reduced without increasing another input and decreasing the output (Charnes, Cooper, & Rhodes, 1981). To determine the (in) efficiency score of school Δ, then :

$$X_{\Delta} = X_0 \qquad (5)$$

and

$$Y_{\Delta} = Y_0 \qquad (6)$$

The $\sum_{i=1}^{n} \theta_i Y_{ij}$ represents the weighted sum of Y_i , i.e. $\theta_A Y_A + \theta_B Y_B + \theta_\Gamma Y_\Gamma + \theta_\Delta Y_\Delta$ with $\theta_A + \theta_B + \theta_\Gamma + \theta_\Delta = 1$ (hypothesizing variable returns to scale)

Assuming that,

$$\sum_{i=1}^{n} \theta_i Y_{ij} = Y_0 \qquad (7)$$

The $\sum_{i=1}^{n} \theta_i X_i$ represents the weighted sums of X_i and assuming that:

$$\sum_{i=1}^{n} \theta_i Y_i = \eta_0 X_0 = X \qquad (8)$$

The efficiency level is:

$$\eta_0 = X / X_0 \qquad (9)$$

If η_0 = 0.8, the efficiency of school Δ is 20% (1 – 0.8 = 0.2). In other words, school Δ must decrease its input by 20% if it is to become efficient, that is to say, to be placed on the segment of the frontier linking school A and school B. Initially, Charnes [31] assumed the scale returns were constant (CRS). In a production process constant returns to scale indicate that production varies in the same proportion as the production factors involved. If all the schools perform optimally, then the CRS hypothesis is appropriate. Banker [35] then modified the CRS model in order to account for situations in which the returns to scale are variable (VRS). This hypothesis means a more flexible frontier can be estimated. Figure 2 shows the distinction between inefficiency (starting measuring from the VRS frontier) and the scale inefficiency (starting measuring from the CRS frontier). The inefficiency corresponds to the inefficiency defined in Eq. 9. However, it seems that at point Δ', the productivity ratio Y_Δ / X is weaker than the maximum ratio Y_Δ / X_A of school A. Even though its efficiency places it at point Δ', the size of school Δ means it cannot have the maximal average production per factor unit. Compared to the latter, which is situated at the optimal size, school Δ suffers from scale inefficiency measured by the relationship X_{Δ}''/ X. Its total inefficiency combines the two forms of inefficiency and is measured by the relationship X_{Δ}''/ X_{Δ}.

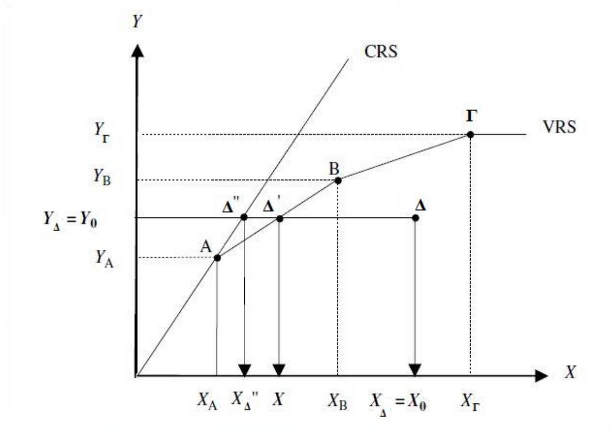

Figure 2. Efficiency and scale efficiency

DATA

The survey took part in North Greece, between November 2016 and March of 2017. In this survey all thirty eight (38) secondary education school units from West North Greece were invited to participate. From these, 38 responded the 29 (76.31% response rate) which from now on will be called as Decision Making Units (DMUs). The region of North West Greece was chosen because of its unique characteristics. According to Elstat (Hellenic Statistical Authority) the average unemployment rate of the region for 2015, was 34.5% while the national average rate in Greece was 24.9%, ranking North Greece the region with the highest unemployment rate in Greece. According to Bradley, Johnes, και Millington (2001), the findings on local labour market conditions are somewhat difficult to interpret. In their study a high incidence of local unemployment appeared to raise school efficiency in secondary education in England. Therefore, it is of high interest whether such findings could be also occur in the case of North West Greece, a region with such high unemployment rate. Despite this high unemployment rate, the corresponding region is characterised by a high GDP per capita (15652 €), which is the second highest in Greece after the Region of Attica. This is another important characteristic to be analyzed as researches show that higher GDP per capita resulting in more efficiency (Afonso & Aubyn, (2006)· Oliveira & Santos, (2005)).

The research tool of this study was designed based on the experience of similar international researches (Kirjavainen & Loikkanen, (1998) · Afonso & Aubyn, (2006)· Avkiran N. K., (2001)· Bradley, Johnes, & Millington, (2001)). The questionnaire consisted of different questions to be answered by the school principal of each secondary school unit. The first category consisted of questions, including general characteristics of the school unit, like the number of students and the number of classes, the number of students of each class and the number of teachers that were offering educational services during the school year 2015 – 16. The second one was referring to all personnel and human resources offering their services in the school unit. This category included not only full-time personnel, but also part-time employees. More specifically, it was referring to the teachers' experience (according to the number of the years they had been teaching) but also to their qualifications (Number of teachers holding a bachelor, a Master's and a Doctorate's degree). Moreover, in this category, there were questions on the number of personnel for other staff categories, like secretarial services, cleaning services and other supportive services. The third category concerned the available equipment of the training unit such as: number of computers available for students and teachers. The fourth category concerned the operating costs of the educational unit. In particular, the questions related to the amount of expenditure for the educational unit for the school year 2015-16 for each of the following categories of expenditure: heating, electricity, communication - internet, water supply, maintenance - general repairs, sports - cultural activities, stationery - office supplies - books, other expenses (postal expenses, pharmaceuticals, cleaning materials and any other expenses not covered by the above categories).

In this study from the above data collected the inputs chosen are: the teacher student ratio, the staff student ratio and the computer student ratio of each educational unit. The output data was collected by the school's Directors and the Regional Secondary Education Office of Western Macedonia. The output (student performance) refers to the student's achievement in the national exams during the school year 2015 – 16 and to their success rate in Higher Education Institutions (HEIs) in Greece.

As Badri & Mourad (2012), note that all relevant surveys agree that the choice of inputs and outputs is particularly important, but it is not clear which are the inputs and outputs of the educational process and at what level they should be measured. At the same time, it is necessary to approach the selected inputs with great precision to represent the characteristics of an educational system, which have an impact on the educational and consequently productive process. However, as this option is limited by availability in databases, there is no unanimous choice of inputs into the bibliography (Hanushek E. , 1986). One important rule of DEA is to avoid the use of highly correlated variables (Badri, Mohaidat, & Mourad, 2014). In particular, if a pair of inputs shows a positive correlation, then something that applies to outputs (Martic, Novakociv, & Baggia, 2009) cannot be included in the efficiency estimation model together. Models with different input / output combinations should ensure the low correlation between the variables involved. This means that during the estimation of efficiency it is important not to include in the same model variables that have a high correlation between them (Badri, Mohaidat, & Mourad, 2014).

In this study, correlation analysis is used to reduce the number of inputs and outputs in each model that will be developed by combining inflows and outputs that do not show correlation (Badri & Mourad, 2012). The correlation analysis revealed that the two outputs, Access Grade and Percentage of Successors do not show significant correlation so they can be used in all possible models at the same time. On the other hand, the pairs of variables, 'Student and student ratio and Computer and student ratio', 'Teacher and student ratio and Percentage of Successors' are correlated and will not be used in any of the analysis models at the same time. The same applies to the 'ratio of auxiliary staff and students' ratio and computer and student ratio' and 'proportion of computers and students and percentage of successful candidates'

In DEA, Cooper, Seiford and Tone (2007) provide two thumb rules for the selection of sample size; a) $n \geq \max(S * P)$, which states that sample size should be greater than or equal to product of inputs and outputs; b) $n \geq 3(S + P)$, states that the number of observation in the data should be at least three times the sum of the inputs and outputs, where n is the sample size (DMU's), S is the number of inputs and P is the number of outputs. Based on these conditions, in the present study the number of school units (DMU's) was (n) = 29, number of inputs was (S) = 3 and number of outputs was (P) = 2. So, in this study the conditions $n \geq \max(3*2)$ and $n \geq 3(3 + 2)$ are respected.

Table 1: DEA Efficiency models (1st stage analysis)					
	Input 1	Input 2	Input 3	Output 1	Output 2
	Teacher - student ratio	Personnel - student ratio	Computer - student	Exams Score	School Success rate
Model 1	X			X	
Model 2			X	X	
Model 3		X		X	
Model 4		X		X	X
Model 5	X	X		X	

FINDINGS

1st stage analysis: In the first stage analysis the main objective was to measure the Technical efficiency of the secondary schools in the region of Western Macedonia in Greece. Using MaxDEA Ultra 6.151 software Technical efficiency are presented in Table 2.

Table 2: Output-Oriented (VRS) – Efficiency Scores					
DMU	Model 1	Model 2	Model 3	Model 4	Model 5
DMU1	0,899	0,866	0,898	0,920	0,907
DMU2	0,993	0,993	0,993	0,995	0,993
DMU3	0,866	0,866	0,888	0,903	0,888
DMU4	0,922	0,922	0,922	0,957	0,922
DMU5	0,994	0,994	0,994	0,995	0,994
DMU6	0,921	0,891	0,876	0,951	0,921
DMU7	1,000	1,000	1,000	1,000	1,000
DMU8	0,887	0,843	0,972	0,972	0,972
DMU9	0,957	0,957	1,000	1,000	1,000
DMU10	0,871	0,864	0,896	0,975	0,899
DMU11	0,944	1,000	0,901	0,973	0,944
DMU12	0,928	0,888	0,953	1,000	0,955
DMU13	1,000	0,937	1,000	1,000	1,000
DMU14	0,908	0,865	0,927	0,952	0,930
DMU15	0,986	0,915	0,910	1,000	0,986
DMU16	0,828	0,819	0,797	0,857	0,828
DMU17	0,909	0,896	0,917	0,945	0,921
DMU18	0,570	0,570	0,570	0,599	0,570
DMU19	0,918	0,927	0,985	0,985	0,985
DMU20	0,920	0,881	0,871	0,906	0,920
DMU21	0,676	0,657	0,657	0,669	0,676
DMU22	0,605	0,605	0,637	0,637	0,637
DMU23	1,000	0,919	0,944	0,997	1,000
DMU24	0,808	0,808	0,808	0,834	0,808
DMU25	0,817	0,817	0,817	0,831	0,817
DMU26	0,829	0,774	0,781	1,000	0,829
DMU27	0,851	0,851	0,851	0,855	0,851
DMU28	0,888	0,820	1,000	1,000	1,000
DMU29	0,853	0,890	0,893	0,893	0,895

According to Table 2, the educational unit, which is defined as the most technically efficient for the school year 2015-16 in all models, is DMU 7 which is a benchmark for all other educational units. Also, there are 17 other training units that have been at least once, benchmarks for the rest of the schools units in the sample in one of the 5 analysis models, ie they have emerged as 100% technicall efficient. Also, the average number of Technically Efficient Educational Units resulting from all 5 models is 4.2, which means that on average about 4 training units out of the 29 sample (13.8%) are characterized as Technically Efficient. The minimum Technical Efficiency displayed was 0.57 while the standard deviation was 0.11 (Model 1, Model 2, Model 3, Model 5). In summary, the above are presented in Table (3).

Table 3: Descriptive statistics of school Technical Efficiency

	Model 1	Model 2	Model 3	Model 4	Model 5
Technical efficient DMUs	3	2	4	7	5
AVE Technical Efficiency	0,881	0,863	0,885	0,917	0,893
STDEV	0,109	0,106	0,112	0,112	0,114
MIN	0,570	0,570	0,570	0,599	0,570

2nd stage analysis: In the second stage analysis, the efficiency scores derived from the first stage analysis were explained in a regression with the environmental variables as independent variables. The independent variables chosen were divided in two categories: the variables from the direct school environment (school size, teacher's experience, teacher's qualifications and per student expenses) and variables from the wider social environment in which each school operates (GDP per capita, unemployment rate and educational level of each school's area).

School size

Analysis showed that the correlation coefficient between the school size and the Technical Efficiency was found to be 0.334, so there appears to be a low positive correlation between these two variables, which is statistically significant ($p = 0.038 < 0.05$). This means that if we increase the school size by 33.4%, we expect to have an increase in the level of the Technical Efficiency. Moving to linear regression analysis, the school size is not a factor that can statistically predict efficiency ($F_{1,27} = 3,393$, $p = 0.076 > 0.05$). More specifically, the size of the educational unit does not significantly affect the Technical Efficiency ($t = 1.842$, $p = 0.076 > 0.05$). International research results are varied concerning the "school size" factor and Barro and Lee (2001) report the school performance and therefore the efficiency of the school units are directly related to the input level of the school unit and in particular to the size of the school unit. In a similar study by Bradley, Johnes, and Millingto (2001), the school unit size seems to have a strong impact on the efficiency of the school as modern and large schools in the urban centers have a higher level of efficiency than those in rural areas and smaller in size. Meunier (2008) reports that the level of efficiency increases as the size of the unit increases, explaining that as the number of students increases in an educational unit, it is possible to save financial resources in specific spending categories to the point of ideal size unit. Kirjavainen and Loikkanen (1998) report that the level of efficiency is less related to the size of the school unit and more to class size. Bradley, Johnes, and Millington (2001) report that educational units that have increased their size have seen their students' school performance improve over time. In another Haug and Blackburn (2013) survey conducted in Australia, the efficiency of secondary school schools in the New South Wales region is being studied and the second level of analysis found that the size of the training unit is a factor that positively affects school performance and increases levels of school efficiency.

Teacher's qualifications

In the present study, the linear regression analysis revealed that the model of efficiency with independent variable the teacher's qualifications is not statistically significant. More specifically, in the linear regression analysis "teachers' qualifications" is not a factor that can statistically predict efficiency ($F_{4,24} = 0,833$, $p = 0,517 > 0.05$). The qualifications of teachers holding a Postgraduate Diploma do not have a significant effect on Technical Efficiency ($t = 1.182$, $p =$ ($t = 1.453$, $p = 0.149 > 0.05$), and the qualifications of teachers holding a second degree do not have a significant impact on the Technical Efficiency ($t = 1.236$, $p = 0.228 < 0.05$). Regarding teacher's qualifications, Rivkin, Hanushek, and Kain (2005) report that the role of teachers is central and particularly important as their quality and skills determine the students' school and learning experience. However, the assessment of quality is not an easy process, and the most frequently occurring variables in the bibliography related to this assessment are the teachers' educational qualifications, years of service and their salary. According to Kirjavainen (2009), Hanushek E. (2003) reports that in most studies conducted, the educational level and teachers' qualifications were not a statistically significant factor. However, in some researches, such as those of Goldhader and Anthony (2007), student performance in assessment tests appears to be higher in the case of students with teachers who have higher educational qualifications. Finally, Rivkin, Hanushek, and Kain (2005) conclude that the observed influence of educational qualifications may have been relatively small in the study of efficiency, yet the contribution of teachers to the whole educational process is particularly important.

Teacher's experience

The variable "Teacher's experience" of each school unit' is a statistically significant factor in Technical Efficiency. In particular, teacher's service years have a positive effect on Technical Efficiency and linear regression analysis has shown that the model with an independent variable, the years of service of teachers can predict the technical efficiency of the school units. The correlation coefficient between the teachers' service years and the technical efficiency, was found to be 0.504, proving a positive correlation between these two variables, which is statistically significant ($p = 0.005 < 0.05$). At linear regression analysis, teachers' experience is a factor that can statistically predict efficiency ($F_{1,27} = 9.188$, $p = 0.005 < 0.05$). ($\beta = 0.008$, $t = 3.031$, $p = 0.005 < 0.05$, $c = 0.781$), so the linear regression model is important in explaining the variability with a factor of determination $R^2 = 0.504$. As shown in the following function, an increase in one year's service life will increase the Technical Efficiency by 0.008.

TE% = 0.008 * Years of service + 0.781

As reported by Hanushek (2003), the Teacher's experience variable, referring to years of service, the majority of researches show a positive correlation with the efficiency of the school units and even statistically significant, indicating that teachers with more experience can contribute positively to school efficiency. On the other hand, the average number of years of service provided by teachers in a Haug and Blackburn (2013) study did not show statistically significant correlation with school efficiency. In the present study, this positive influence of teacher service years on school efficiency can be interpreted with the help of the Teacher Career Model (Huberman, 1995). As reported in Day (2003), Huberman developed an empirical model of the teacher's career cycle which indicates that teachers spend five general phases during their careers. The first phase (1 to 3 years of service) is referred to as the entry into the profession, where the teacher tries to survive in the new professional space and create his/her own social reality. The second phase (4 to 6 years of service) is the phase of stabilization, the sense of maturity, and ultimately the integration of the teacher into the group of colleagues. The third phase (7 to 18 years of service), which is the phase of the training of most educational units with high technical efficiency in this study, is the phase of new challenges. This phase is a period in which it is likely that many teachers will be looking for new challenges, taking on new responsibilities and stepping up their efforts for promotion and development. In this context, the positive influence of teacher service years on school efficiency, which is found in this dissertation, can be interpreted by the fact that most educational units with high technical efficiency have an average service life for teachers between the ages of 7 and 18 (third phase). Thus, during this time of looking for new challenges and opportunities, it seems that teachers can make a positive contribution to school performance and consequently to school efficiency. With regard to the fourth phase (19 to 30 years of service), the teacher reaches a top-level professional level with the basic characteristics of reduced levels of energy and enthusiasm. The fifth and last phase (31 to 40 years of service) of the teachers' career cycle is referred to as a conservative phase where teachers are skeptical of any change, waiting for a 'serene' closure of their professional circle.

Per student expenses

The average level of operating costs per student of secondary school teachers in the Region of Western Macedonia is 105.99 € per year with a standard deviation of 35 €. Higher operating costs per student appearing in a secondary education unit in the Western Macedonia Region are 201.92 €, while the lower operating costs per student are 39.09 €. The correlation coefficient between per student expenditure and technical efficiency was found to be 0.183, meaning that there was no correlation between these two variables ($p = 0.170 > 0.05$). In linear regression analysis, the cost per student is not a factor that can statistically predict efficiency ($F_{1,27} = 0{,}940$, $p = 0{,}341 > 0.05$). More specifically, expenditure per student does not significantly affect the Technical Efficiency ($t = 0.969$, $p = 0.341 > 0.05$). Regarding educational costs, according to the international literature (Fabrino, Valle, & Gomes, 2014), the relationship between public spending and educational outcomes has been the subject of researches that compare the performance of different educational units, taking into account economic and social factors. As Kirjavainen (2009) points out in terms of educational policy, the influence of education spending on student performance and subsequent success in the labor market is a factor that has been extensively studied in the international literature. The most common assumption is that additional resources promote and support the learning process. This study of the influence of educational spending begins in 1966 from Coleman's first research (1966), and since then the research results are mixed. Hanushek E. (2003), a study of similar studies, concludes that in the majority of studies the educational expenditures did not affect school performance and consequently school efficiency as opposed to Hedges and Greenwald (1996), which resulted in the very opposite result. In the present study, the operating costs per student of a training unit do not appear to be a statistically significant factor as they do not significantly affect the Technical Efficiency. More specifically, the performance prediction model with an independent variable operating costs per student is not able to predict statistically significant Technical Efficiency. Levin (2001) argues that in economic analyzes it is important to take these costs into account, since there is also a "significant cost of opportunity for lost productive benefits when one receives education and training rather than being in some other productive work." This may need to be taken into account both by education economists and by politicians, because this has a direct bearing on and affects the efficiency of education programs.

GDP per capita

The GDP per capita of the Region of Western Macedonia for 2015 amounts to 15652€. Considering the correlation between GDP per capita and Technical efficiency, there is no statistically significant correlation between the two variables ($p = 0.242 > 0.05$ and $R = 0.135$) showing correlation analysis between GDP per capita and Technical efficiency. In the linear regression analysis, however, there is no statistically significant effect of the GDP per capita on predicting school efficiency ($F_{1,27} = 0.502$, $p = 0.485 > 0.05$). The GDP per capita of the school area in the Oliveira and Santos research (2005) appeared as a factor that did not affect the technical efficiency of the school unit, as opposed to Afonso and Aubyn (2006) who identified the significant association of the area's GDP per capita the school unit and the educational level of the area where the school unit is located with school efficiency. In particular, they report that areas with higher GDP per capita and more cultured people show higher school performance and higher school efficiency. In the case of the Region of Western Macedonia, there is no significant correlation between the area of the school unit and the educational level of the area where the school unit is located with school efficiency. At the second level of analysis, the Afonso and Aubyn (2006) study, explaining the reasons why some countries lagged in school efficiency, conclude that the low GDP per capita of some countries has a negative impact on school efficiency, unlike other countries with higher GDP per capita.

Educational level of each school's area

The correlation coefficient that emerged between the Educational level of the people living in the school area and Technical Efficiency is very low ($R = 0.016$) and is not statistically significant, therefore there is no correlation between these two variables ($p = 0.467 > 0.05$). The linear regression analysis revealed that the predictive model of efficiency with an independent variable the educational level of the training unit area is not statistically significant ($F_{1,27} = 0{,}007$, $p = 0{,}934 > 0.05$). Regarding the educational level factor of the residents of the school area, in the research by Bessent, Bessent, Kennington and Reagan (1982), the educational level of the parents appears to have a positive effect on school efficiency. An important element of this research is the fact that it also shows the room for improvement of each country in terms of educational efficiency without requiring additional inflows, which is a priority of all countries (Bessent, Bessent, Kennington, & Reagan, 1982). Also, Haug and Blackburn, (2013) report that the area in which the school unit is located and the percentage of students with low socio-economic background appear to have a negative impact on school efficiency. In particular, schools located in the province or in rural areas away from metropolitan centers displayed lower levels of school efficiency. Also low levels of efficiency were also found in schools located in areas of low social and economic level. The research findings of Haug and Blackburn in their study were influenced by education policy in Australia, as the reforms promoted by the Ministry of Education in 2013 were based on analyzes of rational use of inputs from the educational process and the assignment of more sophisticated authority in local government education (Haug & Blackburn, 2013). In the present study, the prediction model of efficiency in the linear regression analysis with an independent variable the educational level of the area of the educational unit can not statistically predict the technical efficiency.

Unemployment rate

According to the Hellenic Statistical Authority (ELSTAT), the average annual unemployment rate for the Region of Western Macedonia for 2016 was 34.5%. The correlation coefficient between the 2016 unemployment rate and the efficiency, was found to be 0.377, proving a low positive correlation between these two variables, which is statistically significant ($p = 0.029 < 0.05$). However, moving to the linear regression analysis level, the unemployment rate for 2016 is not a factor that can statistically significant predict technical efficiency ($F_{1,24} = 3{,}966$, $p = 0{,}058 > 0{,}05$). More specifically, the unemployment rate for 2016 does not significantly affect the Technical Efficiency ($t = 3.228$, $p = 0.058 > 0.05$). Regarding the level of unemployment in the school area, the results of the Bradley, Johnes, & Millington (2001) survey show that the high rate of unemployment shows a positive correlation with school efficiency, yet the researchers report the reservations related to this factor.

DISCUSSION

Results from the first stage analysis show that 4 out of the 29 educational units in each of the 5 DEA models were characterized as technical efficient units. These units became benchmarks for all the others with lower efficiency. Furthermore, for each model, information on the possible slacks of the inputs and the possible projection of the outputs was analyzed. The first stage analysis showed that the average technical efficiency of secondary schools in Western Macedonia for the school year 2015-16 is quite high. Of the 5 models tested, with a different input and output combination, it emerged that on average, 4 educational units in the total of 29 in each analysis model had a level of Technical Efficiency reaching 100%, creating an optimum result for the other educational units with lower efficiency levels. The results of the Technical Efficiency analysis, using output-oriented VRS DEA models, show that despite the high average level of technical efficiency between secondary education units, there are significant differences in several educational units. This result is in line with international literature and research such as that of Di Giacomo and Pennisi (2015) as significant differences in the level of technical efficiency of educational units in the region of Western Macedonia have been identified, due to either the immediate environment or the wider social environment of educational units (Tsakiridou & Stergiou, 2013).

In the second stage analysis, results from regression analysis show that from the independent variables, from the direct school environment, teachers' experience significantly affects school efficiency while teacher's qualifications, school size and per student expenses do not affect school efficiency of secondary education units in the region of Western Macedonia. Concerning the variables from the wider social environment, GDP per capita, unemployment rate and educational level in each school's area didn't show a statistically significant effect on the technical efficiency of the educational units.

Results of this study show that factors that are not under the supervision of the education system and even more of the educational unit are likely to affect school efficiency. This means that apart from the initiatives at the level of the educational unit and more generally at the level of education system, it is necessary to take measures that concern the improvement and development of the wider social environment with which each educational unit interacts. Such policies need to be developed mainly at local and regional level, as the geographic, social and economic characteristics of each region have very wide variations and differences, so each case should be addressed with the necessary care and the corresponding needs. This, of course, implies a more holistic approach to the concept of the educational process, which should be treated as a dynamic process that is constantly changing and is called to meet different needs each time.

It is not enough for an education system to be efficient if it is not effective. An education system that educates and prepares future citizens who develop knowledge and skills that do not meet labor market needs leads young people to unemployment and the education system to be ineffective. This gains even greater weight and is in direct correlation with the results of large surveys since the unemployment factor in the social environment of educational units seems to affect educational efficiency. In the present study, unemployment in the area of the school unit may not have been able to predict technical efficiency as an independent variable in the linear regression model, however, it has shown a statistically significant correlation with technical efficiency. Moreover, the unemployment factor was one of the main reasons for choosing the Region of Western Macedonia as a study area, which is plagued by the phenomenon of unemployment and, in particular, of youth unemployment, so it is likely to be a factor for further analysis.

A limitation of this study is that there was a factor that could not be estimated which is the potential effect of 'tutoring courses' on school efficiency. Teaching outside school with private tutoring courses is a particular feature of the Greek education system as the majority of secondary school students attend such courses to enhance cognitive skills. It is thus a factor which is likely to affect students' performance at school and, consequently, school efficiency, but which cannot be easily estimated as many of these courses are under "shadow economy" so they cannot be investigated.

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