Abstract

The purpose of this paper is to assess the technical efficiency of Tunisian secondary education and to identify the determinants of its performance by using the Programme for International Student Assessment (PISA) 2015 survey. A two stage analysis is conducted; in the first stage we estimate efficiency score of each school by employing data envelopment analysis (DEA) approach. In the second stage, factors affecting school’s efficiency are examined through a Tobit regression analysis. Results show that almost 96.5% of schools are inefficient and on average, Tunisian schools could have increased their results by 27% using the same resources. We conclude that the number of students in the class has a positive effect on the efficiency scores of secondary schools. Furthermore, school responsibility for resource allocation and the socioeconomic background of students’ family influence negatively the school efficiency.

Keywords: economic education, efficiency, data envelopment analysis (DEA), Tobit regression, PISA

JEL Codes: C14, C21, H75

Introduction

The efficiency analysis is a vital managerial control tool for evaluating the degree to which resources are utilized in the process of obtaining desired outputs. Therefore, it is one of the key activities for any enterprise to monitor its efficiency. Aubyn et al. (2009) define efficiency as follows: “Efficiency is essentially a comparison between inputs used in a certain activity and produced outputs. When, with a given amount of inputs or resources, a decision making unit (DMU) attains that level of output or outputs that is the maximum attainable under the existing technology, that DMU is said to be efficient i.e., it operates on the production possibility frontier. When it produces less than what can possibly be attained, the DMU is considered to be inefficient”. The notion of efficiency applies to a remarkably large number of fields. In education, various educational outcomes can result from a variety of different combinations of inputs such as teachers, students, class size, etc. Moreover, in the context of education, efficient use of resources (inputs) occurs when the observed outputs from education (such as test scores) are produced at the lowest level of resource. It is efficiency in education with which this paper is largely concerned.

Under this circumstance, poor performance of school means that there is certainly an inefficiency problem. Consequently, in this paper an efficiency analysis is performed to pinpoint the source of inefficiency and poor performance of public
secondary schools, in order to get a complete picture of the how schools can become more efficient. In fact, the efficiency of DMUs that provide educational services has been a concern in the academic field, the topic is very important considering the amount of money that is devoted to this public sector (e.g. 21.6% of total government expenditure is dedicated to education in 2012).

The efficiency of education systems is measured not by the number of students per class or school, but according to the quality of students' learning. Tunisia has been participating for more than a decade in TIMSS and PISA international assessments. These assessments came to comparatively similar outcomes schools and students attainment in Tunisia is mainly low to very low. For example, according to PISA 2015, among 72 countries Tunisia is ranked 67 in science and reading subjects with 69 in mathematics. Furthermore, when we consider mean performance, Tunisia performed below the OECD average. These results were not in line with the goal of Tunisian government of having better educated pupils. We can describe this situation as a national crisis. The above discussion raises concerns about the quality of the Tunisian education system and its inefficiency. As a result, it becomes crucial to identify the main factors that explain the low quality of the education system in Tunisia.

Therefore, the purpose of this paper is to evaluate the efficiency of Tunisian secondary schools using two stage analyses (DEA-Tobit) and to determine factors that affect the school efficiency by employing the PISA 2015 survey. PISA measures students’ achievement at the end of the compulsory education in reading, mathematics and science literacy. Also, it displays the teachers, schools background and students’ environment issues.

It is expected that such studies would help in identifying the reasons behind the weaknesses of the Tunisian education system and hence would allow the authorities to accommodate education policies in the right way and to act based on the exact needs. The remainder of the paper is organized as follows. Section 2 provides a brief literature review. Section 3 explains the methodology. Section 4 describes the data. Section 5 presents the empirical results and discusses the main finding. Finally, section 6 concludes.

**Literature Review**

An extensive empirical literature has been devoted to the measurement of school efficiency in the last two decades. Among these, Johnes (2015) provided an overview about the use of operational research in education. The author also presented a survey about the problems faced by government, managers and consumers of education and the operation research (OR) techniques that have been applied to improve operations and provide solutions. Also, De Witte and López-Torres (2017) provided an extensive overview of the literature on efficiency in education. The authors summarized the papers on education with the different methodologies applied, the inputs, outputs and contextual variables used as well as the data sources. Thanassoulis et al. (2016) reviewed applications of DEA in secondary and tertiary education. Even if the methodologies used to evaluate schools performances differ, i.e. parametric stochastic frontier analysis – SFA (e.g. Gronberg et al., 2012) or non-parametric data envelopment analysis, DEA or free disposal hull, FDH (e.g. Bradley et al., 2001; Haelermans et al., 2012) there is no consensus on the superiority of one method against the other. For more description of DEA and SFA approaches and their advantages see
the work of Goncharuk (2016). He also, reviewed recent publications concerning efficiency of educational institutions and then grouped them into developed and developing countries. In this study we choose the DEA method. To apply this method, no weight of the input or output variables are required. This is one of the reasons why the use of this method has spread enormously. Moreover, as pointed out by Agasisti (2013) “most of the studies of technical efficiency in schools have used DEA as their methodological approach”.

DEA, originating from Farrell (1957) and popularized by Charnes et al. (1978), is a powerful optimization method that can assess the performance of countries, schools, hospitals, hotels, etc. Moreover, DEA is a non-parametric estimator that uses linear combinations of inputs and outputs of best practice producers to come up with an efficient frontier. Once this frontier is estimated, the performance of the inefficient DMUs can be improved by either increasing the current output levels (output oriented) or decreasing the current input levels (input oriented).

A recent literature about DEA approach provided by Liu et al. (2013) that studied the use of DEA in five main topics: banking, health care, agriculture and farm, transportation and finally education. The authors pointed that education is the application that attracts the most attention. The literature review on education filed using DEA reveals that the latter has been widely applied at all levels of the education sector e.g. Blackburn et al. (2014); Podinovski et al. (2014); Haelermans and Ruggiero (2013); Davutyan et al. (2010); Tyagi et al. (2008) ; Ruggiero (1996); Thanassoulis and Dunstan (1994); Huguenin (2015); Burney et al. (2013), Goncharuk (2018) among others.

Although, two-stage DEA method is widely applied to investigate the impact of explanatory variables on education efficiency. Its statistical foundation has been subject to sharp debate. At the first stage, DEA method is used to estimate the efficiency score for each school. At the second stage, the efficiency scores obtained from the first stage are regressed on covariates that are viewed as representing environmental variables. Since the efficiency scores are bounded, there is no consensus on the method to be applied in the second stage and a variety of regression techniques have been used, including the classic ordinary least squares (OLS) and the maximum likelihood (ML) based probit, logit, and truncated regression (see Simar and Wilson (2007) for an overview). Simar and Wilson (2011) examined the second-stage regressions approaches. They concluded that in the literature, only two statistical models are well-defined and meaningful which are the model proposed by Simar and Wilson (2007) and the model proposed by Banker and Natarajan (2008). They examined and compared the different assumptions underlying these two models. Simar and Wilson (2011) concluded that the second-stage estimation is consistent only under very peculiar and unusual assumptions on the data-generating process that limit its applicability.

Since the efficiency scores obtained from the first stage ranges from zero to one, they are censored variables and thus an estimation using the ordinary least squares (OLS) will provide biased estimates as suggested by Agasisti (2013). A limited dependent variable model is used to avoid this problem in this case the Tobit model is used to estimate the regression equation. For example, Sellers et al. (2010) analyses the efficiency of teaching and research activities using DEA approach and different Tobit models. Hoff (2007) pointed that in most cases the Tobit approach...
will be sufficient in representing the second stage. Despite the fact of the broad use of DEA in the education field worldwide, its application in Tunisia is extremely limited. Essid et al. (2010) addressed especially this objective by focusing on high schools in Tunisia by using DEA-bootstrap approach. They concluded that high schools would be able to deliver the same amount of services with 12% less resources on average. In another study, Essid et al. (2013) raised the question about the school optimal size thus, they developed a procedure to test nonparametric statistical hypothesis concerning the scale efficiency of secondary schools. They found that scale efficiencies are strongly sensitive to sampling variation and contrary to what is known school with small size are not better in performance than school with medium and large size. Essid et al. (2014) used the Malmquist productivity indices to assess the performance of the education sector especially the high schools over the period 2000-2001 and 2003-2004 using quasi-fixed factors. They showed that the productivity in this sector was inactive during this period. Also, Ramzi and Ayadi (2016) evaluated the technical efficiency of 11 public universities in Tunisia in 2009, 2012 and 2013 using two fields of DEA development: weights restrictions and super-efficiency measure. They conclude that number of graduates from Fundamental and Applied Licence influences positively the efficiency scores of universities. Also, the number of students enrolled in Computer sciences, media and telecom influences negatively the efficiency scores of universities. Finally, Ramzi and Ayadi (2016) evaluated the efficiency of 24 Tunisian governorates in basic and secondary education in 1999, 2006 and 2008 using DEA approach. Their results showed that there is no relationship between school resources and student performance.

Despite that above mentioned studies, there is no research work with reference to efficiency analysis of Tunisian secondary schools by taking into accounts the determinants of their efficiency using the PISA survey. We think that this current study will contribute to the literature on education and to present findings which may be with relevance for policy makers to improve the Tunisian educational system.

**Methodology**

In this study, we use a two-stage approach. At the first stage, DEA is employed to estimate efficiency score for each school. We adopt the variable returns to scale (VRS) model, as developed by Banker et al. (1984) and we choose the output oriented model meaning that it maximizes output for a given level of input.

Formally, we assume that the school uses a vector of m inputs \( X = (x_1, \ldots, x_m) \) to produce a vector of s outputs \( Y = (y_1, \ldots, y_s) \). We present individual input and output vectors \((Y_j, X_j)\) for \( DMU_j, (j = 1, \ldots, n) \) as \( x_{ij} (i = 1, \ldots, m) \) and \( y_{kj} (k = 1, \ldots, s) \) respectively.

\( DMU_0 \) is one of the n DMUs being evaluated. The measure of efficiency of \( DMU_0 \) is then obtained by solving the following linear program:
max $\theta$

\[ s.t \quad \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{i0}, \quad i = 1, \ldots, m \]

\[ \sum_{j=1}^{n} \lambda_j y_{kj} \geq \theta y_{k0}, \quad k = 1, \ldots, s \]

\[ \sum_{j=1}^{n} \lambda_j = 1, \quad j = 1, \ldots, n \]

\[ \lambda_j \geq 0 \]

where $\theta$ is a scalar satisfying $\theta \geq 1$. It measures the technical efficiency score of the DMU under evaluation. With $\theta = 1$ indicating that the school is efficient, while $\theta > 1$ implies that the school is inefficient and $(\theta - 1)$ is the proportional increase in outputs that could be achieved, with inputs levels held constant, to become efficient. The scalar $\lambda_j$ represents the associated weighting of outputs and inputs of school $j$.

The performance of a second-stage analysis of DEA efficiencies using a Tobit regression model is a standard practice e.g. Agasisti (2013); Ramzi et al. (2016); Selim and Bursaloğlu (2015); Watanabe and Tanaka (2007); Borge and Naper (2006); Sellers-Rubio et al. (2010), among others. Thus, at the second stage, the efficiency scores are regressed on explanatory variables using Tobit regression. Following Hoff (2007), The Tobit model can thus be defined for school $j$:

\[ \theta^*_j = z_j \beta + \varepsilon_j \quad \text{where} \quad \varepsilon_j \sim N(0, \sigma^2) \]

\[ \theta_j = \begin{cases} \theta^*_j, & \text{if} \quad \theta^*_j \geq 1 \\ 0, & \text{otherwise} \end{cases} \]

where $\theta^*_j$ is an unobserved latent variable and $\theta_j$ is the DEA score, $z_j$ is a vector of explanatory variables and $\beta$ is the vector of parameters to be estimated. STATA software is used to derive results for the two stage analysis.

**Data**

The data used in this research are extracted from the PISA 2015 survey (school and student data set). The initial sample of PISA 2015 data set contains 165 secondary school. 52 schools were dropped because they reported missing data. The choice of secondary schools to assess the efficiency is very important because secondary schools not only occupy a strategic place in the educational system in Tunisia; it is also the link between the primary and the university education levels.

Input variables used in DEA efficiency measurement are the following describing school resources:

i) **Total school enrolment (Nb. Students).** This indicator is obtained from the number of students at school.

ii) **Total number of teachers (Nb. Teachers).** This obtained from the number of full-time teachers at school.

Concerning the output variables and following established practice, we adopt measures of direct educational and commonly used outputs, PISA test scores. Students
from Tunisia were evaluated with the same set of questions to be solved. In fact, a large number of studies use specially the standardized test scores as output. Agasisti et al. (2014) pointed that “such a choice represents today the standard for analyzing school efficiency”, as in Coco and Lagravinese (2014); Blackburn et al. (2014). Hence, the output variables are: The maximum test scores in mathematics (MAXM), the maximum test scores in reading (MAXR), and the maximum test scores in science (MAXS).

Inputs are extracted from PISA school data set, while outputs are extracted from PISA student data set. Descriptive statistics of variables used in the first stage are presented in Table 1.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nb. Students</td>
<td>738.9027</td>
<td>363.9789</td>
<td>130</td>
<td>1850</td>
</tr>
<tr>
<td>Nb. Teachers</td>
<td>66.12389</td>
<td>28.32847</td>
<td>1</td>
<td>130</td>
</tr>
<tr>
<td>MAXM</td>
<td>427.4271</td>
<td>46.72737</td>
<td>333.405</td>
<td>599.8073</td>
</tr>
<tr>
<td>MAXR</td>
<td>412.707</td>
<td>49.97501</td>
<td>302.161</td>
<td>555.4847</td>
</tr>
<tr>
<td>MAXS</td>
<td>426.0821</td>
<td>37.31521</td>
<td>349.5718</td>
<td>560.3505</td>
</tr>
</tbody>
</table>

Table 2. Description of Exogenous Factors for Second Stage Analysis

<table>
<thead>
<tr>
<th>Category</th>
<th>Variable</th>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Family</td>
<td>Economic, social and cultural status</td>
<td>ESCS</td>
<td>The index of economic, social and cultural status consists of three sub-components: the higher parental occupation, the higher parental education expressed as years of schooling and the index of home possessions, as well as books in the home.</td>
</tr>
<tr>
<td>Student</td>
<td>Sense of belonging at school</td>
<td>BELONG</td>
<td>Students’ sense of belonging was measured by asking them about their feelings about school as a place. It measures the sense of belonging in terms of whether the students feel they fit in at school.</td>
</tr>
<tr>
<td>School</td>
<td>Class size</td>
<td>CLSIZE</td>
<td>Our analysis is at school level, “class size” is measured as the average class size in a school.</td>
</tr>
<tr>
<td>School</td>
<td>School responsibility for resource allocation</td>
<td>RESPRES</td>
<td>The index of the relative level of responsibility was derived from six items of the school principals’ report regarding who had considerable responsibility for tasks related to resource allocation (Selecting teachers for hire, firing teachers, establishing teachers’ starting salaries, determining teachers’ salaries increases, formulating the school budget, deciding on budget allocations within the school).</td>
</tr>
</tbody>
</table>

In the second stage we attempt to identify the potential factors that affect schools’ efficiency. An educational system is well known to be very complex due to the multiplicity of its components (schools, students, parents, educators and principals) that is why, we apply our model to data extracted from the PISA 2015 survey including variables related to different levels of secondary education (students, family and school). We classified those exogenous factors into three categories that reflect: Family
characteristic, Student characteristic and School characteristic. A description of variables used in the second stage analysis is given in Table 2.

We should note that the socioeconomic status (ESCS) variable is used in the most of the papers dealing with the determinants of education efficiency (schools or students) such (Masci et al., 2016; Huguenin, 2015). Moreover, the effect of class size on education performance is a largely addressed topic in the literature and the existing studies show different results (see Agasisti, 2013). Finally, The previous literature on the determinants of schools’ efficiency using OECD-PISA data did not address specifically the issue of the sense of belonging at school (belong) and the index of school responsibility (respres) influence. To the best of our knowledge, it's the first time that such variables are used in the literature for school efficiency.

The Tobit model takes the following form:

$$\hat{\theta}_j = \beta_0 + \beta_1 ESCS_j + \beta_2 BELONG_j + \beta_3 RESPRES_j + \beta_4 CLSIZE + \epsilon_j,$$

where $\hat{\theta}_j$ is an estimator of the efficiency score obtained at first stage from model (1). The descriptive statistics of variables used in the second stage are presented in Table 3.

### Table 3. Descriptive Statistics of Second Stage Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>ESCS</td>
<td>-0.8670149</td>
<td>0.6923293</td>
<td>-2.600047</td>
<td>0.8727561</td>
</tr>
<tr>
<td>BELONG</td>
<td>-0.1826848</td>
<td>0.3634487</td>
<td>-0.73015</td>
<td>3.22942</td>
</tr>
<tr>
<td>CLSIZE</td>
<td>27.55752</td>
<td>6.144013</td>
<td>13</td>
<td>53</td>
</tr>
<tr>
<td>RESPRES</td>
<td>-0.535031</td>
<td>0.6053255</td>
<td>-0.7946</td>
<td>2.8245</td>
</tr>
</tbody>
</table>

### Results and Discussion

**First Stage Analysis**

We evaluate the efficiencies of 113 Tunisian secondary schools for the school year 2015-2016 using model (1). The average output efficient score of all secondary schools equals 1.27 which indicates that with the same level of inputs used, the average DMU seems obtaining a performance about 27% less than it should if it was on the efficiency frontier. On average, Tunisian secondary schools could have increased their results by 27% using the same resources (number of full time teachers and number of students). The average score and standard deviations are, respectively: 0.796 and 0.084 and the value of the estimated efficiency range between 1 and 1.552.

The first stage analysis reveals that the efficiency frontier is composed by 4 schools number (23, 56, 61 and 158). The four efficient secondary schools have some special characteristics. School 56 has the best score in mathematics, reading and science so it should be in the production possibility frontier. School 23 has the least number of full-time teachers. While school 61 has the minimum number of students compared to the other schools in the sample. Lastly the students’ performance of school 156 in the mathematics, reading and science are greater than the average. Furthermore, it’s significant to note that the size of those schools is smaller than the average.
The worst efficiency score registered is 1.552 attributed to the school 93. It’s important to report that this school has the minimum score in mathematics test compared to the other schools in the sample with scores in science and reading lower than the average. However, this DMU can improve its efficiency by increasing the current scores in mathematics, reading and science by 55.2% using the same number of students and full-time teachers. School 3 is not far from the frontier with efficiency score equal to 1.046. Thus, this school must increase the students’ performance in the
three literacy scales by only 4.6% to become efficient. As it can be noticed from the above discussion, the power of the DEA approach is its ability in determining the level of increase in the outputs for the school to become efficient.

Table 4 presents the descriptive statistics of the obtained results in the first stage. The efficiency scores estimated with model (1) are listed in Table 5.

**Second Stage Analysis**

In the second stage, the efficiency scores obtained in the first stage are regressed on factors affecting the school's efficiency. In this stage, multicollinearity could be a problem because it can increase the variance of the coefficient estimates and make it very sensitive to minor changes in the model. Therefore, to test for potential multicollinearity in the data set, the variance inflation factors (VIF) test is used (Table 6). A VIF of 5 or greater indicates the presence of multicollinearity. Hence, a regression model containing all the explanatory variables mentioned above is run. The mean VIF is equal to 1.03425. Thus, it can be concluded that the results of our model are unlikely to be distorted by multicollinearity. Furthermore, the correlation matrix presented in Table 7 suggests that no correlation were found among the four explanatory variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Tolerance</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>ESCS</td>
<td>0.990</td>
<td>1.010</td>
</tr>
<tr>
<td>BELONG</td>
<td>0.980</td>
<td>1.020</td>
</tr>
<tr>
<td>CLSIZE</td>
<td>0.947</td>
<td>1.056</td>
</tr>
<tr>
<td>RESPRES</td>
<td>0.952</td>
<td>1.051</td>
</tr>
</tbody>
</table>

Table 7. Correlation Coefficient Matrix of Explanatory Variables

<table>
<thead>
<tr>
<th></th>
<th>ESCS</th>
<th>BELONG</th>
<th>CLSIZE</th>
<th>RESPRES</th>
</tr>
</thead>
<tbody>
<tr>
<td>ESCS</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BELONG</td>
<td>0.092</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CLSIZE</td>
<td>0.000</td>
<td>0.090</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>RESPRES</td>
<td>0.042</td>
<td>0.041</td>
<td>-0.208</td>
<td>1</td>
</tr>
</tbody>
</table>

Thus, using DEA efficiency scores estimated from the first stage we evaluate the significance of four exogenous factors in explaining the level of schools’ efficiency.

The results shown in Table 8 suggest that the variable ESCS have significant explanatory power. This result is in line with most of the previous literature (e.g. Masci et al., 2016). Schools with a high ESCS show higher efficiency, so that the ESCS is positively associated with school efficiency. This is a result confirmed also in the previous literature. If the number of students from advantaged family increases, the school performance also increase. Since, as indicated by Masci et al. (2016) the ESCS is directly proportional to family income, which weighs positively, and is inversely proportional to the percentage of disadvantaged students, which weighs negatively. Moreover, class size plays an important role for efficiency, attending schools with overcrowded classes has a negative relationship with secondary school efficiency. Suggesting that smaller classes are associated with higher achievement, contrarily to
the findings of Masci et al. (2016).

Table 8. Estimation Results of the Regression

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficients</th>
<th>Std. errors</th>
<th>t-statistic</th>
<th>P &gt; t</th>
</tr>
</thead>
<tbody>
<tr>
<td>ESCS</td>
<td>-0.1042962</td>
<td>0.0143938</td>
<td>-7.25 *</td>
<td>0.000</td>
</tr>
<tr>
<td>BELONG</td>
<td>-0.0200202</td>
<td>0.0271135</td>
<td>-0.74</td>
<td>0.462</td>
</tr>
<tr>
<td>CLSIZE</td>
<td>0.0029703</td>
<td>0.0016446</td>
<td>1.81 **</td>
<td>0.074</td>
</tr>
<tr>
<td>RESPRES</td>
<td>-0.102038</td>
<td>0.0219714</td>
<td>-4.64 *</td>
<td>0.000</td>
</tr>
<tr>
<td>Constant</td>
<td>1.036967</td>
<td>0.0476861</td>
<td>21.75</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Notes: *Indicates significance at the 1%; ** Indicates significance at the 10%

A glance on recent statistics provided by the Tunisian Education Ministry shows that the average class size in secondary schools has decreased to reach 25.5 pupils in 2015 compared to 33 students in 2000. Looking at the student ‘characteristics, there is no relevant variable, since that the sense of belonging at school is not significant. The final variable that we report is the responsibility for school allocation. The coefficient of RESPRES is statistically significant at the 1% level. This indicates that when the level of responsibility of school principal increases, school efficiency increases too. A possible explanation is that this may be due to the fact that the Ministry of education had a considerable responsibility for tasks related to resource allocation. Therefore, school with less or no responsibility in allocating resources has poor performance.

Conclusion
The objective of this paper is twofold. First, it analyses the efficiency of secondary schools using a non-parametric technique namely data envelopment analysis (DEA), and second, it examines the determinants of school’s efficiency using Tobit regression using data extracted from the latest PISA assessment in 2015 on a sample of 113 Tunisian secondary schools.

The results of the first stage show that on average, Tunisian secondary schools have to increase their achievement by almost 27% using the same number of students and number of full-time teachers to become efficient. Furthermore, our results show that 96.5% of schools are functionally inefficient.

We consider simultaneously three areas of information related to school, students and family. This allows us to identify the most influential variables that should be acted on to improve secondary school efficiency. From the second stage results it emerges that variable related to school and family characteristics have significant explanatory power. The efficiency is positively related to socio economic status of parents and to level of responsibility attributed to school principal. However, the class size has a significant negative effect on the efficiency level.

These findings have an important policy implication. To achieve the goal of increased education efficiency in Tunisia, policy measures should concentrate on giving more responsibility to school principal in tasks related to resource allocation because, a school principal is a primary leader in a school building. He can provide leadership that affects every teacher and student. Also, particular attention should be given to students that their parents are disadvantaged socially, educationally and economically. Moreover, by decreasing the class size, this makes students more competitive and therefore enhances school efficiency. This work does not take into
account undesirable factors such as dropout phenomena since education efficiency represents a powerful technique to address this problem. Hence, incorporating these factors in the analysis is a possible extension for the present paper. We can also consider additional factors affecting school efficiency.

References
analysis approach”, *Economics of Education Review*, Vol. 29 No. 4, pp. 589-596.


