

## **Estimating the Technical and Scale Efficiency in Swiss Secondary Education**

**Djily Diagne**

*University of Geneva, CH-1211 Geneva, Switzerland*

Email: Djily.Diagne@unige.ch

**Abstract:** Data envelopment analysis (DEA) technique is used to estimate the technical and scale efficiency of Swiss secondary schools. Results suggest that there is room for improvement in terms of efficiency in resource utilization but the average size of schools under consideration is not far from the optimal size. Socio-economic environment of pupils and the status of the teacher are significantly associated with technical efficiency.

**Keywords:** Secondary Education; Efficiency; Data Envelopment Analysis; Switzerland

**JEL Classification Number:** I21, D24, H52

### **1. Introduction**

During the last decades, increasing attention has been paid to the efficiency of educational production around the world. From an economic perspective, schooling is considered as an important instrument for affecting both the national economy and the distribution of individual income. It is also assumed to generate various externalities and school spending represents the largest expenditure in most state budgets (Hanushek, 1996). Hence, whether schools are efficient or not is a crucial question for policy-makers and the public, in general.

Two main approaches have been proposed in the economic literature to evaluate the efficiency of schools: the parametric method (e.g., stochastic frontier analysis or SFA, see Aigner et al., 1977) and the non-parametric method (e.g., data envelopment analysis or DEA). While SFA is based on econometric analysis, DEA involves mathematical programming. A major drawback of the SFA approach is the imposition of strong *a priori* assumptions on the production process. The DEA method has several advantages. It gives a single measure of performance, which can take into account several dimensions of school activity since it has the ability to handle multiple inputs and outputs simultaneously. Furthermore, it does not require an *a priori* specification of a functional form (i.e Cobb-Douglas) for the input-output relations. Based on minimal assumptions, DEA uses the principles of linear programming theory to calculate an efficiency score for each school. It uses the data from all schools in order to construct a best practice frontier that envelops the data, and measures each school's distance from the frontier. Finally, one of the well-known

advantages of DEA, which is relevant to our study, is that it works particularly well with small samples, as long as the number of inputs is not too high in comparison to the sample size (Evanoff & Israilevich, 1991). DEA has been widely employed to measure the efficiency of educational organizations [(see, for example, Cooper and Rhodes (1978); Färe et al. (1989); Ray (1989); Primont and Domazlicky (2006); Chakraborty and al. (2001); Grosskopf et al. (1999); Ruggiero and Vitaliano (1999); Kirjavainen and Loikkanen (1998); Waldo (2001); Bonesroning and Rattso (1994); Johnes (2006), Bradley et al. (2001); Athanassopoulos and Shale (1997); Abbott and Doucouliagos (2003) and Doucouliagos and Abbott (2008)]. The present study constitutes the first attempt to evaluate the technical and scale efficiency of schools in Switzerland using DEA.

Switzerland is a Confederation of 26 cantons and has a largely decentralised education system. Most decisions on the running of primary and secondary schools are taken at the cantonal level. Federal, state, and local spending on public schools amounted to CHF 25.8 billion in 2003, about 6% of national income. In spite of the high public investments in the education sector, reports from international organisations (see, the OECD PISA comparative study) show that Swiss pupils are not performing very well in international tests of achievement, and that increased spending has not lead to notable gains in school performance. These facts highlight the need for measuring the productive efficiency in public secondary schools in Switzerland. We limit the study to the public academically-oriented gymnasiums called *maturité* located in the French-speaking part of Switzerland. These secondary schools provide a general education and conclude with a school-leaving certificate called *maturité*, which opens the way to university entrance.

## 2. DEA methodology

DEA is a linear-programming method based on Farrell's (1957) seminal work that was later popularized by Charnes et al. (1978). This original model assumes constant returns to scale (CRS) in its production possibility. Banker et al. (1984) later suggested an extension of the CRS model to account for variable returns to scale (VRS) situations. Since the DEA model is well established and extensively applied in the literature, its discussion is limited in this article. A variety of more recent extensions can be found in Coelli et al. (1998) and Cooper et al. (2000).

Let us assume that there is data on  $K$  inputs and  $M$  outputs on each of  $N$  DMUs (i.e. schools). For the  $i$ th DMU these are represented by the vectors  $x_i$  and  $y_i$ , respectively. The  $K \times N$  input matrix,  $X$ , and the  $M \times N$  output matrix,  $Y$ , represent the data for all  $N$  DMUs. The input oriented measure of a particular DMU, under CRS, is calculated as:

$$\text{Min } \theta_i \theta, \quad \text{s.t. } -y_i + Y\lambda \geq 0, \theta x_i - X\lambda \geq 0, \lambda \geq 0$$

where  $\theta$  is a scalar representing the efficiency score for the  $i$ th school and  $\lambda$  is an  $N \times 1$  vector of constants. If  $\theta = 1$  the school is efficient as it lies on the frontier, whereas if  $\theta < 1$  the school is inefficient and need a  $1 - \theta$  reduction in the inputs levels to reach the frontier. The linear programming is solved  $N$  times, once for each DMU in the sample, and a value of  $\theta$  is obtained for each DMU representing its efficiency score. The model specified above has an assumption of constant returns to scale and is only appropriate when all schools are operating at an optimal scale. Banker et al. (1984) suggested the use of variable returns to scale (VRS) that decompose OTE into a product of two components. The first is technical efficiency under VRS or pure technical efficiency (PTE) and related to the ability of managers to utilize schools resources. The second is scale efficiency (SE) and refers to exploiting scale economies by operating at a point where the production frontier exhibits CRS. The CRS linear programming is modified to consider VRS by adding the convexity  $M1'\lambda = 1$ , where  $M1$  is an  $N \times 1$  vector of ones. The technical efficiency scores obtained under VRS are higher than or equal to those obtained under CRS and SE can be obtained by dividing OTE with PTE (i.e.  $SE = OTE/PTE$ ). By comparing the VRS and CRS frontiers one can identify scale inefficiency of a school. The non-increasing returns to scale (NIRS) technology is needed as additional information to determine whether a particular school is experiencing increasing or decreasing returns to scale. Thus, if the efficiency score for a particular school under VRS and NIRS are identical, then that school can be said as operating under decreasing returns to scale (DRS). On the other hand, if the score under VRS is not equal to the NIRS score, then the school is operating under increasing returns to scale (IRS).

### 3. Data

Data used in this study are based on a survey conducted in March 2001 from 27 public *maturé schools* located in the French-speaking part of Switzerland. This represents around 25% of the total number of public *maturité* schools in Switzerland. The *maturité* schools output is measured by the percentage of candidates that obtains the *maturé certificate* (MATU) that allows continuation to university. Five inputs are included in the analysis. The input variable (TEACHER) represents the number of full-time equivalent teachers per pupil. The variable (EXPERIENCE) refers to the experience of teachers as measured by the percentage of them with over ten years of teaching experience. (EDUCATION) represents the education of teachers measured by the percentage of teachers with at least a master's degree, (TENURE) represents the last discretionary input variable and refers to the percentage of teachers having a permanent status. These variables represent different components of instruction and are frequently used as measures of the provision of educational services. They are of particular interest to economists since they can be manipulated by school administrators. We also use a non-discretionary input

(NSCHOLARSH) representing the proportion of pupils who did not hold a scholarship during the school year 1999-2000 in order to take into account the influence of the family background characteristics of pupils.

We develop five DEA models to assess the performance of schools. The output used in the first four models is the percentage of students who pass their grade (MATU). In Model 1, we measure inputs with 2 variables that are under management's control: the number of full-time equivalent teachers per pupil (TEACHER) and the experience of teachers (EXPERIENCE). In model 2 we include an additional input over which management has no direct control, the percentage of pupils who do not hold a scholarship (NSCHOLARSH).

Model 3 uses the number of full-time equivalent teachers per pupil (TEACHER) and the percentage of teachers having a permanent status (TENURE) as inputs while model 4 includes the education of teachers (EDUCATION) and the number of full-time equivalent teachers per pupil (TEACHER).

In order to investigate the issue of returns to scale, we use a fifth model in which all the variables are measured in volumes instead of percentages or proportions. Like model 1, model 5 uses two inputs: the number of full-time equivalent teachers (NUMTEACH) and the total number of years of experience of all the teachers at the school (NUMEXPER). The output is measured by the number of students who pass their grade (NUMMATU).

We adopt an input-oriented approach in all the models because we believe that this option is in line with the Swiss policy-makers' emphasis on cost-efficient resource usage in education in recent years. In the first four models, we assume only constant returns to scale (CRS). A variable returns to scale DEA model is also run to investigate scale issues (model 5).

#### **4. Empirical Results**

The results from model 1 are summarised in Table 1. Based on the DEA analysis of 27 secondary schools, 6 (22%) are found to be technically efficient. The mean efficiency score of the sample is 85 percent with a standard deviation of 11 percent. The minimum efficiency score is 66 percent. Overall, our findings suggest that the schools in our sample could deliver the output with only 85 percent of the current inputs. Or, it could reduce current inputs by 15 percent if all schools were as efficient as the 6 benchmarks identified by the model. For comparison reasons, a mean technical inefficiency of 15% is broadly in line with results derived from a number of previous empirical studies. For example, Ray (1991) estimated 14.63% inefficiency for public schools in Connecticut. Primont and Domazlicky (2006) found average inefficiency of 22.5% in Missouri schools. Kirjavainen

and Loikkanen (1998) estimated inefficiency in Finnish senior secondary schools to be between 18.9% and 22.1%. It should be noted that, while results from these studies are similar in mean efficiency, the range of efficiency and the proportion of efficient schools may differ significantly across studies.

**Table 1: Summary Statistics of the Four Models (CRS)**

	Model 1	Model 2	Model 3	Model 4
Mean efficiency	85.47	93.94	84.88	77.42
Standard deviation	11.17	7.60	9.14	15.45
Maximum efficiency score	100.00	100.00	100.00	100.00
Minimum efficiency score	66.03	73.12	71.23	48.78
Number of efficient schools (%)	6 (22%)	12 (44%)	4 (15%)	5 (18%)

Model 1 does not account for environmental factors. Thus, it may penalize “good” performers who operate in an unfavourable external environment and reward “poor” performers who operate in favourable external environment. In order to deal with this situation, we include in model 2 an environmental variable represented by the proportion of pupils who do not hold a scholarship during the school year 1999-2000. This variable is used as a proxy for family socioeconomic status. Economic deprivation has often been cited as a significant factor affecting student performance because more educated and higher earning parents may provide better resources and environment for learning at home. Summary statistics of the second model are also shown in Table 1. After controlling for socioeconomic background influences, the average efficiency increases by nine percentage points, from 85 per cent to 94 per cent. At the same time, the number of efficient schools doubles from 6 to 12. This confirms the importance of controlling for the external operating environment. In particular, the increase in average efficiency suggests that without controlling for the operating environment, the schools operating under unfavourable circumstances are penalized. In a similar vein, the decrease in the standard deviation of the efficiency scores (from 11.17 to 7.60) may reflect the fact that without controlling for the external environment, the efficiency scores of schools that operate in unfavourable circumstances are biased down.

Table 2 presents the results from input-oriented DEA model 5 which is used to investigate the issue of returns to scale. The DEA is performed with CRS and the results compared to those from the VRS model. Scale efficiency is then calculated as the ratio of the CRS efficiency to the VRS efficiency. Four schools (15%) are best practice under CRS and 7 (26%) under VRS. The mean technical efficiency of the sample is 82 per cent and 86 per cent under CRS and VRS assumptions, respectively. This implies that on average, schools

could reduce their inputs by 18 per cent and 14 per cent and still maintain the same output level. Scale efficiency is high with an average of 97 per cent. Its interpretation allows for some interesting remarks. The observed mean scale efficiency implies that the average size of Swiss secondary schools under consideration is not far from the optimal size, although an additional 3% efficiency gain would be feasible if they adjust their operation to an optimal scale. Four schools are actually operating at the most productive scale where CRS apply and scale efficiency equals one. Upon further examination, we find that the remaining 23 schools are scale inefficient and evenly distributed between increasing and decreasing returns to scale. In particular, 12 schools are operating under decreasing returns to scale and 11 are experiencing increasing returns to scale. Efficiency analysis theory suggests that the latter are too small schools to take full advantage of scale and need to increase their size in order to improve efficiency, whereas the former are larger schools that have expanded more than necessary and thus would be better off by reducing their size.

**Table 2: Decomposed Technical Efficiency Scores and Nature of Returns to Scale (Model 5)**

Technical efficiency (CRS scores)	Pure technical efficiency (VRS scores)	Scale efficiency	Returns to scale
Mean = 82.47	Mean = 86.39	Mean = 96.79	CRS = 4
Std. dev. = 13.03	Std. dev. = 12.51	Std. dev. = 5.17	DRS = 12
			IRS = 11

After presenting the technical efficiency measures, the next step is to identify the determinants of efficiency using a two-stage procedure. First, efficiency scores from input-oriented DEA models 1-4 (CRS) are regressed on a set of environmental and organisational variables using ordinary least squares (OLS) and Tobit regressions. A positive relationship with efficiency scores is expected since pupils who do not hold a scholarship are socio-economically advantaged. Others hypotheses are that the coefficients of EXPERIENCE, EDUCATION, and TENURE are expected to be positively related to performance.

In terms of goodness of fit, the overall regression with the traditional OLS model has a reasonable explanatory power, as is witnessed by the  $R^2$  values, ranging from about 22 to 53 percent. The coefficient of the socio-economic background variable is positive in all models and almost always statistically significant. This result is consistent with theoretical expectations. The education variable provides positive effects on technical efficiency, but the coefficient is rarely statistically significant. The experience variable is not consistently signed and is always insignificant. This finding supports results from Hanushek (1986) and Cooper and Cohn (1997). Finally, it is interesting to note that the tenure variable is negatively related to efficiency and the effect is generally significant. This result is in

contrast to Waldo (2001). The censored distribution of DEA efficiency scores makes the Tobit model the appropriate technique to use in order to explore the sources of technical efficiency of schools, according to several authors (see, Bradley et al., 2001). However, results from Tobit regression are similar to those obtained from OLS.

### **5. Concluding Remarks**

Results of this study show that the schools under consideration are highly scale efficient and the major cause for their inefficiency is technical capability rather than scale of operations. The econometric estimations used in the second stage indicate that school efficiency is significantly related to socioeconomic factors. This finding has serious implications since environmental factors are beyond the control of the school administrator. Perhaps the more important result is the unexpected negative sign of the tenure variable. This suggests that a high proportion of teachers with permanent status may be detrimental to school performance. Obviously, the analysis reported in this paper is only a first attempt to evaluate the efficiency of Swiss schools and should be interpreted with caution. There remains ample room for additional studies corroborating or falsifying the present results.

### **References**

- Aigner, D.J., Lovell, C.A.K., and Schmidt, P, 1977, Formulation and Estimation of Stochastic Frontier Production Function Models. *Journal of Econometrics* 6, 21-37.
- Athanassopoulos, A and Shale E, 1997, Assessing the comparative efficiency of Higher Education Institutions in the UK by means of DEA. *Education Economics* 5, 117-134
- Avkiran, N. K, 2001, Investigating technical and scale efficiencies of Australian universities through data envelopment analysis. *Socio-Economic Planning Sciences* 35, 1, 57-80.
- Banker, R. D., Charnes, A. and Cooper, W.W., 1984, Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis, *Management Science* 30, 1078-1092.
- Bonesrønning, H. and Rattsø, J., 1994, Efficiency variation among the Norwegian high schools: consequences of equalization policy, *Economics of Education Review* 13, 289-304.
- Bradley, S., Johnes, G. and Millington, J. 2001, The effect of competition on the efficiency of secondary schools in England, *European Journal of Operational Research* 135, 545-568.

- Chakraborty, K., Biswas, B. and Lewis, W., 2001, Measurement of Technical Efficiency in Public Education: A Stochastic and Nonstochastic Production Function Approach, *Southern Economic Journal* 67, 889-905.
- Charnes, A., Cooper, W.W. and Rhodes, E., 1978, Measuring the efficiency of decision making units, *European Journal of Operational Research* 2, 429-444.
- Cooper, S.T. and Cohn, E., 1997, Estimation of a Frontier Production Function for South Carolina Educational Process, *Economics of Education Review* 16, 313-327.
- Cooper, W., Seiford, L. And Tone, K., 2000, *Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software*, Boston, Kluwer Academic Publishers.
- Evanoff, D. and Israilevich, P. 1991, Productive Efficiency in banking, *Economic Perspectives* 15, 11-32.
- Färe, R., Grosskopf, S. and Weber, W. L., 1989, Measuring school district performance, *Public Finance Quarterly* 17, 409-428.
- Farrell, M. J. 1957, The measurement of productive efficiency, *Journal of the Royal Statistical Society* 120, 253-281.
- Hanushek, E.A. 1996, Measuring investment in education, *Journal of Economic perspectives* 10, 9-30.
- Hanushek, E.A., 1986, The Economics of Schooling: Production and Efficiency in public Schools, *Journal of Economic Literature* 24, 1141-1177.
- Johnes, J. 2006, Data Envelopment Analysis and its Application to the Measurement of Efficiency in Higher Education, *Economics of Education Review*, 25, 273-288.
- Kirjavainen, T. and Loikkanen, H.A., 1998 Efficiency Differences of Finnish Senior Secondary Schools: An Application of DEA and Tobit Analysis, *Economics of Education Review* 17, 377-394.
- OECD 2002, *Regards sur l'éducation* : Paris
- Primont, D. F. and Domazlicky, B. 2006, Student Achievement and Efficiency in Missouri Schools and the No Child Left Behind Act, *Economics of Education Review* 25, 77-90.
- Ray, S.C. 1991, Resource-use efficiency in public schools: A study of Connecticut data, *Management Science* 37, 1620-1628.
- Waldo, S. 200, *Municipalities as Educational Producers – An Efficiency Approach*, Mimeo, Lund University.