EFFICIENCY OF JUNIOR HIGH SCHOOLS AND THE ROLE OF PROPRIETARY STRUCTURE

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Abstract

In this paper we deal with the role of proprietary structure in explaining efficiency within the Italian school industry. We analyze a sample of 497 schools located in Piemonte, a region in the North-Western part of the country, distinguishing between public, private for-profit and private nonprofit schools. In stage one of the analysis, we provide robust estimates of efficiency scores, using the two most widely known techniques in applied works, namely Data Envelopment Analysis (DEA) and Stochastic Frontiers (SF). In stage two, we suggests that proprietary structure matters in explaining efficiency. Nonprofit schools are more efficient than public ones, whereas for-profit counterparts are outperformed by public producers. Moreover, we find that foreign and disabled students affects negatively efficiency, raising concerns for cream-skimming practices among private producers. Finally, school size is another important determinant of efficiency.

J.E.L. Codes: I20, D24, L31.

Keywords: efficiency, privatization, school choice.

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1. Introduction

In western countries, the organization of the compulsory school system has been the subject of a widespread policy discussion over the last years. In Italy, recent reforms have been undertaken to increase the effectiveness and the efficiency of the – mostly public – system of compulsory education. Some critics of the Italian reform process emphasized that higher benefits (in terms of efficiency and effectiveness of the school system) could be gained getting rid of the *de facto* state monopoly of education and increasing the role of private schools that, in the opinion of these commentators, tend to be more efficient than public ones. Private provision of education is free in Italy, but only a limited number of students attend private schools because of their cost; on the contrary, public education is provided free of charge. According to opponents of the public compulsory school system, state monopoly could be dismantled introducing competition between private and public schools and making students (and their parents) free to choose the school they prefer. Competition could be created in two different ways, just to mention the most widespread and debated proposals: public lump sum subsidies could be given to private schools, as some politician advocate or, alternatively, a voucher system could be introduced so as to make it indifferent – as far as cost is concerned – attendance of a private or a public school to students and their families.

While the debate over "freedom of choice" and competition in the school system is now becoming a crucial political issue, very little research has been undertaken in Italy to measure the impact of alternative systems (private and public) of education provision on students performance. In his widely quoted survey of the literature on school efficiency, Hanushek (1986) observes that "there appears to be no strong or systematic relationship between school expenditures and student performance", whereas "family background is clearly very important in explaining differences in achievement"; intuitively, better educated and wealthier parents have children that perform better on average. Of course, as parental background cannot be managed by schools, there appear to be no easy policy recommendations in order to improve efficiency. However, when one compare public and private schools, Hanushek notes that private schools outperform public ones. Two basic criticism relate to this finding. First, as family background is important in determining efficiency, one can argue that private schools superior efficiency simply reflect a bias in student composition: better educated and wealthier parents prefer to enroll their children in private schools. Second, it might well be that the distinction between public and private schools (i.e. the difference in terms of proprietary structure) hides other most important and structural differences (e.g. a systematic diversity in teaching staff). As Hanushek puts it, "in this area, the evidence is very incomplete".

With this paper we try to partially fill this gap. In order to asses the impact of proprietary structure on efficiency, we adopt a two-stage procedure. In stage one we measure technical efficiency of junior high schools located in the Italian northern region of Piemonte, a large and highly populated area where about six million people live. To the best of our knowledge, this is the first attempt to estimate technical efficiency of schools using Italian data. To measure efficiency we use both a DEA and a stochastic frontier approach, specifying different production functions. Our results are encouraging, since efficiency estimates are robust to different techniques and model specifications. In stage two we explore what lies behind differences in efficiency scores. According to classic results in the literature, differences in efficiency could be determined by the number and the characteristics of the students enrolled as well as by the proprietary structure (public, nonprofit or for profit) of the school. We expect an inverse correlation between efficiency and the number of foreign and disadvantaged students attending schools, because of possible lower performance of foreign students and higher need of teachers for the disadvantaged ones. We also expect a direct correlation between efficiency and the size of schools, because of the decreasing impact of fixed costs. On the contrary, we do not have any *a priori* hypothesis concerning the impact of the proprietary structures on technical efficiency. In fact, several reasons may explain the superiority of public, nonprofit or for-profit organizations in this respect. For example, theoretical results emphasize the role of the non-distribution-of-profit constraint (NDC) in generating incentives in nonprofit organizations. On the one hand, it is often assumed that the NDC reduces the incentive to exploit under-informed consumers providing services of lower quality to increase profits; of course, this increases efficiency. On the other hand, the NDC may reduce the incentive for managers to exercise effort and control costs; hence, it reduces efficiency. Our empirical analysis could therefore be useful to verify the hypothesis (implicit in the Italian political debate) that private (both for-profit and not-for-profit) schools are more efficient than public ones.

Our findings show that proprietary structures do matter. Private nonprofit schools appear to be more efficient than public ones; on the contrary, private for-profit schools are less efficient that their public counterparts. These differences in efficiency between private and public schools could back the idea of introducing competition in the school system. As showed by Hoxby in several papers, competition *among* public schools and competition *between* public and private schools increases productivity of public producers. Hence, private provision of education could be justified basically through a yardstick competition argument: private schools stimulate efficiency.

As expected, our findings also indicate that the presence of disadvantaged and foreign students decreases efficiency. As these students concentrate in public schools (and – as far as foreign students are concerned - in a very limited number of private for-profit schools) some concern may be raised about a cream-skimming approach of private institutions. Moreover, our findings show that size matters in determining efficiency. From a policy point of view this means that small schools (schools with a limited number of students) should be closed to increase the overall efficiency of the school system. However, such a measure would raise an efficiency-equity trade-off. In fact, smaller schools are more likely to be located in areas (such as mountain or rural villages) where income and wealth are lower than average.

The structure of the paper is the following. In section 2 we briefly describe the Italian system of compulsory education. Our sample is described in section 3.1, while in section 3.2 we specify the different models and techniques (DEA and stochastic frontiers) used to estimate technical efficiency. Section 3.3 reports our findings on efficiency scores of junior high schools in Piemonte. We analyze the impact of different proprietary structures on technical efficiency of schools in section 4. Section 5 briefly concludes the paper.

2. The Italian school industry

Following recent reforms that have been target of much criticism, the Italian system of compulsory education is now undergoing major changes that will most likely influence its performance and efficiency in the near future. Nonetheless, since data used in this paper refer to 1998, it is useful to describe the characteristic of the Italian system of compulsory education in the late nineties. In 1998, education was compulsory for all Italian children from age 6 to 14. During their 8 years long career of compulsory education, students were required to attend primary (elementary) schools from age 6 to 10 (grades 1 to 5) and junior high schools from age 11 to 14 (grades 6 to 8). In 1999 a new law extended compulsory education to age 15.

As far as provision of educational services is concerned, state-run schools played a major role. In fact, in 1996 (latest figure available), 92% of the Italian students from age 6 to 10 attended a state-run primary school while, in 1997, 96% of students from age 11 to 14 attended a state-run junior high school[1]. Therefore, private schools, most of them nonprofit institutions run by religious orders, played a modest and marginal role in the Italian system of education. The only exception is represented by non compulsory nursery schools (pupils from age 3 to 5) where public schools were in short supply and private schools enrolled about 65% of all students; about two third of these students attended a school run by a religious order.

In 1998, public schools were still considered as local branches of the central administration; therefore, they did not enjoy any degree of autonomy or self-government as far as budget or management was concerned. Public schools were funded by a complex mixture of funds coming from both the central and local governments. While the central government took care of running costs and the cost of teaching personnel, local governments bear the expenses for building maintenance; non teaching personnel was funded by a complex blend of central and local public funds. In 1999, a new law recognized some degree of autonomy to the Italian public schools; according to this law, each school will get legal personality as well as higher freedom to organize its

[1] Data referring to non compulsory senior high schools are not very different; in fact, in 1997 about 93% of the Italian students attended a senior high school run by public authorities, mostly the state.

supply of services and to innovate teaching techniques and curricula. Nonetheless, public schools will not be free to hire teachers and non teaching personnel. In fact, teachers working in public schools are public employees hired in nationwide contests; their wages - established at the national level and directly disbursed to individuals by the central administration – do not differ in relation with individual skills or effort, but only with "seniority". Moreover, regulation allows for the minimum and maximum ratio between teaching personnel and students. As a consequence, one would not expect great variations in the cost structure of public schools. However, within the system of public compulsory education, students and their families enjoy some degree of choice. In fact, the Italian system of public compulsory education is quite close to what Cohn (1997) called a "public schools choice model" were students are allowed to attend any public school, regardless of attendance zone or district lines.

Compulsory education is free for all students attending public schools. Students and their families can also opt out for private schools. However, while public schools are free of charge, attendance of a private school requires direct payment of fees and charges with (limited) fiscal deductibility. In fact, although private education is guaranteed by the Italian constitution, private school get very little funding either from the state or local authorities, both directly and indirectly. High direct cost is, most likely, the primary reason explaining the limited attendance of private schools in Italy. Private schools are free to organize as they like as far as curricula and teachers are concerned. Nonetheless, only schools following strict national regulations (including number, skills and wages of teachers, availability of building, free access of students, democratic governing structure) can be considered as part of the national system of education and have their degrees certified and recognized by the state. A certified degree is necessary to enter higher levels of public education and to gain access to public jobs. As a consequence of this strict system of regulation one may expect that differences in cost and efficiency between public and private schools should not be very relevant.

3. The estimation of efficiency

In this section, we concentrate on the estimation of technical efficiency. We provide efficiency scores using different estimation techniques and different models.

3.1. Data description

Our full sample consists of 497 junior high schools (grades 6 to 8) located in Piemonte, an Italian region in the north-western part of the country. Sample year is 1998 and data are cross-section, aggregated at the school level. We consider public and private schools, distinguishing between private for-profit and private nonprofit ones so that (in stage two of our analysis, see section 4) we will be able to fully account for the effect of proprietary structure on schools' efficiency. Public schools include institutions run by either local or central authorities. Given the absence of a clear definition of nonprofit organization in the Italian law (Barbetta, 1997), we considered all schools run by religious orders as nonprofit institutions and schools run by private lay and secular organizations as for-profit institutions.

In order to estimate efficiency we described the process of education as a production function where inputs are transformed into outputs. Of course, this description of education is highly problematic (e.g. Barr, 1998). In fact, while one could easily measure the amount of certain inputs (teachers, students, equipment, buildings, etc.) used in the "production process", their quality is hard to assess; moreover, the amount of other inputs (such as the natural ability of the students or the role of parental background) cannot be measured smoothly. Likewise, the education output is hard to define and measure; as some authors clearly stated, "since there is no single definition of a 'good' education, there is no unambiguous measure of output. We can measure test scores, but (a) such measure are imperfect even in their own terms, and (b) education outputs are much broader than such technical benefits" (Barr, 1998, p. 322). Furthermore, the causal relationship between inputs and outputs is also hard to determine. Despite all these limitations, describing the education process with the production function approach is quite common in the literature dealing with efficiency estimation. In this paper, we model the production technology using a simple multi-input–single-output production function; hence, schools are viewed as producers that seek to maximize the number of graduates using the minimum required amount of resources. This objective function can be thought as a minimum condition for all the different schools and can encompass profit maximization for for-profit schools and welfare maximization for both nonprofit and public schools. Our general model can be represented by equation (1):

(1)

where G represents the number of graduates in the final examination; T represents the total number of teachers, TD the total number of teachers taking care specifically of disabled and disadvantaged students, A the total number of employees with administrative duties and S the total number of other non-teaching personnel; Z represents a vector of environmental variables that might influence schools production, namely cultural background and income (see below). We are forced to this oversimplification as no data is available neither about the "quality" of inputs used in the production process, nor about the "quality" of the educational services (the output) provided by the schools belonging to our sample.

As far as input variables are concerned, our inputs closely mirrors those normally used in empirical analysis of educational services production functions. As far as the output variable is concerned, the lack of test scores represents the most severe limitation of our analysis, as score results can be interpreted as a proxy for the "quality" of educational services produced. In Italy all students take the same final graduation exam, regardless of the school - public or private - attended but failures are negligible. Even if individuals passing their final graduation exam get scored, score results are not available. Therefore, we could not measure scores on a continuos scale, but only on a "fail" or "pass" basis. In this respect, our model is quite close to the one used by Kirjavainen and Loikkanen (1998), who consider both the number of students who pass their grade and the number of graduates in matriculation examination as output variables in their analysis of Finnish senior secondary schools. Of course, both measures are imperfect proxies of individual students' achievements. However, considering the sample of Italian junior high schools, our output measure can be interpreted as a reliable proxy of students' attainments. In fact, the junior high school degree represents a *minimum* requirement to access the unskilled labor market, that in Italy accounts for more than half of total jobs available.

Table 1 provides some descriptive statistics, distinguishing between public producers and private ones. Public schools represent the vast majority of the sample (423 producers). Among private providers, 61 are nonprofit schools, while just 13 are for-profit firms. Nonprofit schools are mainly run by religious orders, whereas for-profit schools are represented by secular organizations. On average, public schools enroll more students than private ones. The number of disabled and foreign students is larger for public schools than for private nonprofit ones, whereas private for-profit producers provide their services to more foreign students than their public counterparts. Data seem to suggest the existence of "cream skimming": private nonprofit producers enroll only the least problematic students. Nonprofit providers also show more students per teacher than public and private for-profit schools; this may suggest a better use of resources compared with their competitors or, at the opposite, lower "quality" of the education process.

Table 1. Descriptive statistics

	All sample (497)		**Public (423)**		**Nonprofit (61)**		**For-profit (13)**	
Variables	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***
Students	174.2	114.2	190.4	114.1	89.9	57.6	42.6	22.2
Disabled	4.5	4.7	5.3	4.7	0.04	0.2	0.2	0.5
Foreign	3.8	5.8	4.3	5.8	0.3	0.7	4.9	11.7
Graduates	59.5	40.1	65.0	40.2	31.6	20.1	12.9	6.9
Teachers	27.4	15.9	30.2	15.5	11.4	3.4	9.8	2.4
Teachers for disabled	2.7	2.9	3.2	2.9	0.03	0.1	0.0	0.0
Administr. staff	2.3	1.6	2.4	1.6	1.7	1.8	1.7	1.0
Non-teaching staff	5.3	3.1	5.9	2.8	1.5	1.6	0.9	1.3
Student/teachers ratio	6.56	2.58	6.53	2.50	7.2	3.0	4.2	1.7

3.2 Model specification

In order to obtain robust estimates of efficiency scores, we use two different methodologies of estimation and specify two different models. The environmental variables Z define the only difference between the two models. Model 1 includes a proxy variable for parental educational background, represented by the share of persons with a BA degree out of the total population living in the school neighborhood. We do expect a positive influence of this variable on educational attainments. Model 2 considers the total number of bank branches active in the school neighborhood as a proxy of population income and wealth. Again, we expect income and wealth to have a positive impact on the output of the education process. We decided to consider parental background and population income separately because of the possible correlation between the two variables. However, it is still debated whether the causality goes from growth (i.e. income) to schooling (i.e. parental background) or the other way round (e.g. Romer, 1993 and Bils and Klenow, 2000).

We used the two most common methodologies applied in the literature to estimate our models. In particular, we first estimated our production functions using the Data Envelopment Analysis (DEA) methodology introduced by Banker et al. (1984). DEA is a linear programming technique that does not require the specification of the function f(.) in equation (1) and it is usually labeled as a non-parametric methodology. However, classic DEA models do not allow researchers to distinguish between statistical noise and inefficiency; in this sense, DEA estimate a *deterministic* frontier. Of course, this implies that DEA is very sensitive to the presence of outliers in the data. Banker (1993) provided DEA with a statistical foundation, by showing that it offers maximum likelihood and consistent estimators under very mild conditions, when modeling multi-input-single-output production functions. As we do not have any a priori assumption, we specify the production function either with constant returns to scale (CRS) or with variable returns to scale (VRS). From equation (1), DEA frontier estimators accounting for VRS can be written as (e.g. Banker, 1993):

(2)

where **X**=(T, TD, A, S, Z) represents the input vector and the λ's are the optimal weights to be determined to define the "best practice" deterministic DEA frontier. The linear programming model that accounts for CRS can be obtained from equation (2) by simply dropping the constraint $\sum_j \lambda_j=1$.

We then estimated our models following the methodology introduced by Aigner et al. (1977). Differently from DEA, the stochastic frontier (SF) technique requires the specification of function f(.) in equation (1); in this respect, SF represents a parametric methodology for efficiency estimation. In particular, we specify our production functions as Cobb-Douglas stochastic production frontiers:

(3)

where C measures the level of technology in the industry; E is a composed error term that takes into account both white noise (v) and economic inefficiency of firms (u); the remaining variables are defined as earlier.[2] The specification of the composed error term E clearly identifies another striking difference between DEA and SF, since SF estimate a *stochastic* frontier. Starting from equation (3) and taking logs, we get the following specification:

(4)

where lower case letters represent logs. MLE estimators of the model are presented in table 2. We assume that inefficiency is distributed as a half-normal random variable. As usual in stochastic frontier models, λ represents the ratio between standard deviation of

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[2] A translog specification produced fairly similar results in terms of efficiency scores; regression estimates and efficiency estimators are not reported here.

the two random variables collected in the error term, respectively inefficiency and statistical noise.

Table 2. Regression results[(a)]

Variables	Model 1 SF	Model 2 SF
Constant	1.167 (6.358) ***	1.652 (16.458) ***
Teachers	0.734 (15.817) ***	0.708 (16.366) ***
Teachers for disabled	0.077 (1.935) *	0.102 (2.732) ***
Administrative staff	0.058 (1.377)	0.054 (1.390)
Other non teaching staff	0.079 (2.091) **	0.068 (1.822) *
% population holding a B.A.	0.106 (3.498) ***	-
Nr. bank branches	-	0.064 (5.732) ***
Nr. Observations	497	497
Log-L	-297.5	-284.4
λ	3.127 (7.520) ***	3.512 (7.832) ***
LR-test[(b)]	1.704	0.0046

(a) MLE. Asymptotic t-ratios in parentheses. Lev. of significance: 1% ***, 5% **, 10% *.
(b) Test the hypothesis $\sum_i \beta_i = 1$ in educational services production function; critical values $\chi^2(1)$.

Almost all of the coefficients show the expected sign and are statistically significant. Teachers represent the input that gives the highest contribution to the production of educational services, whereas administrative staff seems not to affect the provision of education. Both environmental variables (parental background and income) affect the production process positively. Unfortunately, we have no further data to analyze the relationship between growth and education more in depth. However, our findings strongly suggest that the two variables play the same role and are somewhat correlated. We also test the null hypothesis H_0: $\sum_{j=1,\ldots,5} \beta_j = 1$ against the alternative H_1: $\sum_{j=1,\ldots,5} \beta_j \neq 1$ using a Likelihood Ratio test. As reported in table 2, we found no evidence to reject H_0 at conventional significance levels.

3.3. Empirical findings on efficiency scores

DEA and SF provides estimates of efficiency scores for each school in the sample. Estimates of technical efficiency for the two models and the two different methodologies are reported in table 3. As expected, mean efficiency is higher in the case of SF estimators than DEA estimators. In fact, stochastic frontier models distinguish inefficiency from statistical noise, while deterministic frontier models do not. SF estimators are defined as in Jondrow et al. (1982); they represent the conditional expectation of inefficiency u given the observed error term e. As shown by Waldman (1984), E[u|e] provides unbiased but inconsistent estimators of inefficiency. DEA mean efficiency ranges from 0.34 in the case of CRS to 0.42 when considering VRS with model 1 and 0.51 with model 2. Mean efficiency determined with SF methodology is 0.63 in both models. Interestingly, different types of proprietary structure show statistically different results.[3] On the one hand, mean efficiency for the sub-sample of public schools closely mirrors the results obtained for the whole sample. On the other hand, mean efficiency is systematically higher with respect to the entire sample when considering the sub-sample of not-for-profit schools, while it is generally lower looking at the sub-sample of for-profit schools.

Table 3. Efficiency estimators

Models	**All sample (497)**		**Public (423)**		**Nonprofit (61)**		**For-profit (13)**	
	Mean	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
DEA 1 CRS	0.34	0.17	0.34	0.16	0.35	0.23	0.17	0.08
DEA 1 VRS	0.42	0.19	0.41	0.18	0.52	0.26	0.50	0.25
DEA 2 CRS	0.34	0.17	0.34	0.15	0.37	0.24	0.18	0.10
DEA 2 VRS	0.51	0.26	0.50	0.26	0.54	0.27	0.52	0.29
SF 1	0.63	0.18	0.63	0.17	0.65	0.20	0.40	0.18
SF 2	0.63	0.18	0.64	0.17	0.64	0.20	0.39	0.19

Table 4 shows the correlation coefficients between different estimators calculated considering different model specifications. Correlation between estimators obtained with the same methodology range from 0.982 (SF) to 0.549 (DEA VRS). The results suggest that the ranking of schools in terms of efficiency seems not to be affected by small changes in model specification (e.g. the environmental variables). Even the nature of returns to scale does not seem to affect the results in DEA frontiers. In fact, correlation between CRS and VRS DEA estimators is 0.742 in the case of model 1 and 0.615 in the case of model 2. Considering the nature of returns to scale, efficiency

[3] Kruskal-Wallis test rejects the hypothesis of common distribution for the three groups in almost all the cases; the only exception is represented by scores obtained with DEA VRS in model 2.

estimators obtained using either SF or DEA appear to be fairly robust as well.[4] In particular, correlation range from 0.702 (model 1 DEA CRS and model 1 SF) to 0.611 (model 2 DEA CRS and model 1 SF). As should be expected, correlation between estimators obtained with different methodologies are much lower when one considers DEA VRS models. Following these considerations, in the remaining of the paper we use scores obtained with DEA CRS and with SF models only. Our aim is to understand the role of proprietary structure in shaping the efficiency in the industry of educational services.

Table 4. Correlation among different estimators

	DEA 1 CRS	DEA 1 VRS	DEA 2 CRS	DEA 2 VRS	SF 1	SF 2
DEA 1 CRS	1	0.742	0.624	0.314	0.702	0.693
DEA 1 VRS		1	0.468	0.549	0.470	0.447
DEA 2 CRS			1	0.615	0.611	0.673
DEA 2 VRS				1	0.202	0.261
SF 1					1	0.982
SF 2						1

4. What causes efficiency: a second stage analysis

Robustness of our efficiency scores estimators encourages a second stage analysis on the determinants of efficiency. Since we want to analyze the impact of proprietary structure of schools on technical efficiency (EFF), we begin our analysis by defining the dummy variable PRIVATE, that takes value 1 when the i-th school is private (either nonprofit or for-profit) and value 0 otherwise. Previous empirical papers show mixed evidence on the role played by a private proprietary structure on efficiency. For instance, Kirjavainen and Loikkanen (1998) find that "somewhat surprisingly, private schools are less efficient than public schools", whereas the survey by Hanushek (1986) seems to suggest that private schools perform better than public schools. In order to control for other determinants of schools' efficiency, we consider in our second stage analysis also school size (as measured by the number of students N) and the number of

[4] Recall that in the case of stochastic frontiers we found no evidence to reject the hypothesis $\Sigma_i \beta_i = 1$.

disabled (D) and foreign (F) students. We do not have any clear *a priori* expectation on the school size variable: Kirjavainen and Loikkanen (1998) find that school size is insignificant in explaining efficiency; Deller and Rudnicki (1993) show that "increasing school size may be a hindrance to student performance"; finally, standard microeconomic arguments would suggest a positive effect of increasing size (at least up to a certain point) in the presence of fixed costs. In this respect, school size could influence efficiency in a non linear fashion; hence, we test for a quadratic relation including the number of students squared (N^2) among our regressors. On the other hand, the number of disabled and foreign students should negatively affect efficiency, as it should be more difficult for a disabled (or a foreign) to get her degree. Our general Tobit model estimating the causes of efficiency can be represented as follows[5]:

(5)

where **X**=(PRIVATE, N, N^2, D, F) and u_i is a N(0, σ^2) error term. We also allow for the presence of heteroskedasticity by specifying the variance of the error term as:

(5 bis)

Efficiency scores estimators derived using either DEA CRS or SF represent our dependent variables EFF. Regression estimates are in table 5.

Empirical findings suggest that the proprietary structure affects efficiency. As in most previous empirical papers, private schools seem to perform better than public schools. School's size does matter: the higher the number of students, the more efficient is the school. Interestingly, this relationship is nonlinear: efficiency rises with school size, but

[5] In a more general model we also interact the dummy variable PRIVATE with the number of foreign and disabled students. However, a Wald test did not find evidence to reject the hypothesis of joint insignificance of the coefficients associated with these additional variables at standard levels.

at a decreasing rate. As expected, the number of disabled and foreign students affects efficiency negatively.

Table 5. Second stage analysis (Tobit models) (a)

Variables	**Mod. 1 DEA**	**Mod. 2 DEA**	**Mod. 1 SF**	**Mod. 2 SF**
Constant	0.189 (6.914) ***	0.309 (9.927)***	0.423 (18.448) ***	0.432 (18.432) ***
PRIVATE	0.038 (1.910) *	0.013 (0.611)	0.089 (3.388) ***	0.058 (2.264) **
N	0.001 (6.277) ***	0.0006 (2.753) ***	0.001 (8.547) ***	0.001 (8.443) ***
N^2	-0.000001 (-3.122)***	-0.0000009 (-2.273) **	-0.000001 (-4.471) ***	-0.000002 (-4.871) ***
D	-0.007 (-2.630) ***	-0.006 (-3.036) ***	-0.005 (-4.537) ***	-0.006 (-4.328) ***
F	-0.003 (-1.658) *	-0.004 (-2.267) **	-0.002 (-2.040) **	-0.003 (-2.731)***
(b)	0.170 (28.285) ***	0.241 (19.535) ***	0.211 (15.838) ***	0.205 (15.658) ***
ℵ (c)	-0.0003 (-1.771) *	-0.002 (-8.542) ***	-0.002 (-8.314) ***	-0.002 (-6.136) ***
Nr. Observations	497	497	497	497
Log-L	158.77	174.08	284.08	254.59
Model χ^2(d.f. 5)	103.32	37.45	224.33	188.15

(a) MLE. Asymptotic t-ratios in parentheses. Lev. of significance: 1% ***, 5% **, 10% *.
(b) Estimated disturbance standard deviation.
(c) Heteroskedasticity term.

We further explore the issue of proprietary structure by splitting our variable PRIVATE in two different dummies, namely NPO and FPO, that takes value 1 respectively when the i-th school is a nonprofit organization or a for-profit firm and value 0 otherwise. In fact, simply opposing private schools to public schools could veil very different behaviors within private producers. Hence, we estimate a new Tobit model by modifying the set of regressors in Eq. (5); in this case **X**=(NPO, FPO, N, N^2, D, F).[6] We allow for heteroskedasticity also here, specifying the variance of the error term as in the previous Eq. (5 bis). Results reported in table 6 are robust among the four regressions. Estimated coefficients are statistically significant and signs are fairly stable to variations in the dependent variable. Efficiency seems to be affected in two opposite directions: nonprofit schools seem to be more efficient than public ones, while for-profit schools are more inefficient.

[6] Also in this case, we started from a more general model that included the dummy variables NPO and FPO interacted with the number of disabled and foreign students. We tested the joint significance of the coefficients associated with these additional variables using a Wald test. We found no evidence to reject the null hypothesis of these coefficients being jointly equal to zero.

One possible interpretation of these results relies on the different roles the two kinds of schools might play in the market for educational services. Suppose we have high talented and low talented students, with the former interested in school's selectivity and the latter preferring a less challenging environment. Public educational services should then be designed so as to account for both types of students. Nonprofit schools could compete with public schools to attract the most talented students, offering better quality services or increasing selectivity. Indeed, the "cream skimming" approach of nonprofit schools that was observed earlier in the paper could be interpreted as the result of this competition between private nonprofit and public schools. On the other hand, for-profit schools could deliberately attract *less* talented students, by offering a less competitive environment. This behavior implies a sort of monopoly for less talented students and could explain the lack of efficiency that characterizes for-profit schools. The different roles of public, nonprofit and for-profit schools may be linked to variations in the funding mechanism between public and private schools. While public schools get by the state a lump sum contribution not strictly related to the amount of services provided, private schools compete with each other and their funds come from fees. Most likely, nonprofit and for-profit institutions act on different markets. However, since we cannot control for output (and input) "quality", we cannot reject a very different interpretation. Nonprofit schools may simply use a lower amount of inputs (when compared to public schools) and therefore produce output of different (lower) "quality". Given the nature of our final score tests (that does not allow to measure scores on a continuous scale) this lower "quality" may be mistaken as higher efficiency.

As for other determinants of efficiency, results does not change. The size of school still matters: in fact efficiency rises, even at a decreasing rate, as the number of students increases. As expected, the presence of disadvantaged students, either disabled or foreign, reduces schools efficiency and shows a clear efficiency–equity trade-off.

Table 6. Second stage analysis (Tobit models) [(a)]

Variables	Mod. 1 DEA	Mod. 2 DEA	Mod. 1 SF	Mod. 2 SF
Constant	0.195 (7.088)***	0.316 (10.244)***	0.430 (19.333)***	0.439 (18.924)***
NPO	0.058 (2.876)***	0.036 (1.700) *	0.113 (3.925)***	0.083 (2.955)***
FPO	-0.069 (-0.824)	-0.146 (-1.287)	-0.080 (-1.272)	-0.100 (-1.674)*
N	0.001 (5.900)***	0.0005 (2.533)***	0.001 (8.399)***	0.001 (8.079)***
N^2	-0.000001 (-2.865)***	-0.0000008 (-2.148)**	-0.000001 (-4.349)***	-0.000001 (-4.568)***
D	-0.0067 (-2.589)***	-0.005 (-3.009)***	-0.005 (-4.452)***	-0.006 (-4.253)***
F	-0.003 (-1.481)	-0.003 (-2.069)**	-0.001 (-1.780)*	-0.002 (-2.481)**
(b)	0.169 (27.901) ***	0.238 (19.318) ***	0.206 (15.783) ***	0.200 (15.583) ***
N (c)	-0.0003 (-1.644)	-0.002 (-8.340)***	-0.002 (-7.963) ***	-0.002 (-5.879) ***
Nr. Observations	497	497	497	497
Log-L	161.73	177.93	289.95	259.82
Model $\chi^2(6)$	109.26	45.15	236.07	198.61

(a) MLE. Asymptotic t-ratios in parentheses. Lev. of significance: 1% ***, 5% **, 10% *.
(b) Estimated disturbance standard deviation.
(c) Heteroskedasticity term.

5. Concluding remarks

In this paper we provide a first attempt to measure efficiency in the Italian school industry. We concentrate on a sample of 497 junior high schools located in Piemonte, distinguishing between public, private for-profit and private nonprofit producers. Following most of the empirical literature on efficiency in schooling, we model the process of education as a production function where inputs (teachers, other personnel and environmental variables such as parental background or income) are combined in order to produce outputs (graduates). Our efficiency scores estimates appear to be robust to different model specifications and to different methodologies (Data Envelopment Analysis and Stochastic Frontiers). This encourages a second stage analysis where differences in efficiency are explained by the proprietary structure, the size of the schools and the presence of disabled and foreign students. Our main result suggests that proprietary structures do matter and that previous empirical papers could miss very different behavior within private producers. In particular, we show that private nonprofit schools are more efficient than public ones, whereas private for-profit producers are outperformed by public ones. Both the size of the schools and the presence of disadvantaged students are other determinants of efficiency. This raises important efficiency-equity trade-off that should be taken into account when revising the actual system of public funding. In this respect, it is worth noting that competition – not just the presence of private institutions - may increase efficiency. For instance, competition (and efficiency) may increase when private (and public) schools are funded according to the number of students they serve. On the contrary, lump sum contributions not related to the amount of services produced clearly do not provide schools with incentives to pursue efficiency.

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