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Abstract

To study education as a complex production process in a noisy and heterogeneous setting, this paper suggests to using a stochastic frontier model estimated by a local maximum likelihood approach (LMLSF). The LMLSF smoothly combines the virtues of the non-parametric Data Envelopment Analysis model and the semi-parametric Stochastic Frontier model. Additionally, by the LMLSF approach one can deduce the effectiveness of resources by examining the impact of inputs on the frontier. Indeed, while efficiency estimations (i.e., doing the things right) received considerable attention in the literature, the analysis of effectiveness (i.e., doing the right things) is less explored. The approach is illustrated on a sample of Dutch primary education pupils. We examine the effectiveness of instruction time, experience of the teacher, and student care (both social worker and psychologist) on educational attainments of native and non-native students.

Keywords: Stochastic Frontier Analysis; Data Envelopment Analysis; Local Maximum Likelihood; Education; Student care

JEL-classification: C14, C25, I21

1 Introduction

By developing several approaches to estimate the performance of observations (see Fried et al., 2008), the literature on frontier analysis has been paying significant attention to the relative efficiency level of units. The methodologies can broadly be grouped in two families. On the one hand, the semi-parametric stochastic frontier approach (SFA; Meeusen and Van Den Broeck, 1977), and on the other hand, the non-parametric Data Envelopment Analysis (DEA; Charnes et al., 1978) approach.[1] Both families have their intrinsic advantages and disadvantages. We do not intend to exhaustively compare both approaches, but on the contrary, focus on some crucial aspects on which they differ.

(Semi-)parametric frontier approaches are appealing thanks to (1) their smooth decomposition of noise and inefficiency, and (2) the parametrization of the marginal effect of inputs on the frontier. The former advantage is attractive as it allows the researcher to model the noise in the data. The noise may arise from unobserved heterogeneity or measurement errors. If noise is neglected, the efficiency estimations will be biased. Some applications are more vulnerable to noise than others. For example, within education there might arise significant noise due to for the researcher unobserved characteristics. The latter advantage is appealing as insights in the marginal contribution of performance drivers further foster performance as the scarce resources could be allocated to the inputs with the largest added value.

However, the advantages of SFA models come at the cost of explicit assumptions on (1) the functional form of the frontier (e.g., Cobb-Douglas, Translog, Fourier), (2) the distribution of noise (e.g., half-normal, truncated normal) and (3) the distribution of inefficiency. A survey by Yatchew (1998) clearly indicates that economic theory almost never specifies a precise specification of the functional form of production functions. As such, the imposition of an arbitrary functional specification of the production frontier can result in erroneous inference, which in turn biases the estimates and makes the analysis intricate.

The deterministic nonparametric DEA approaches are appealing as they impose only mild assumptions on the production technology. The nonparametric models 'let the data speak for themselves' in that the data determine the functional specification of the frontier. As such, the DEA models 'solve' the specification issue of the SFA models. However, the traditional DEA models (1) are unable to separate inefficiency from random noise, (2) have estimates which are vulnerable to outlying observations, and (3) are not designed to provide information on the marginal influence of inputs on the frontier. These shortcomings make them often heavily criticized in 'standard economic literature'.

[1] We follow the literature in classifying Free Disposal Hull (FDH; Deprins et al., 1984) and other variants as DEA models, see Fried et al. (2008).

It is clear that the drawbacks of the SFA models correspond to the benefits of the DEA model, and vice versa. Therefore, recent semiparametric and nonparametric alternatives for frontier analysis combine the merits of both SFA and DEA, and, as such, simultaneously limit (or even eliminate) the discussed drawbacks. We briefly discuss some suggested models. Fan et al. (1996) proposed a two-step pseudo-likelihood estimator that does not impose an *a priori* specification of the production frontier. However, the model still suffers from distributional assumptions on the decomposition of noise and inefficiency. Cazals et al. (2002), Aragon et al. (2005) and Daouia and Simar (2007) propose to nonparametrically estimate partial frontiers that are robust to outliers. A two-stage approach as in Florens and Simar (2005) can be used to parametrize the marginal frontier impact of inputs. However, as extensively discussed in Kuosmanen et al. (2009), noise is not the same as outliers and, therefore, the robust nonparametric approaches are still deterministic. Kuosmanen and Kortelainen (2006) show that DEA and stochastic frontier are restricted cases of shape constrained nonparametric least squares estimation. By the use of Stochastic Nonparametric Envelopment of Data (StoNED), the virtues of a stochastic frontier and a deterministic, nonparametric approach can be combined. Similar to DEA, monotonicity and convexity can be composed. Similar to SFA, noise and efficiency are separated, and information on the marginal impact of the inputs can be computed. Nevertheless, the StoNED approach still implies an *a priori* global specification of inefficiency and noise distribution.

An alternative approach has been suggested by Kumbhakar et al. (2007). They propose to localize the parametric frontier model, based on the local maximum likelihood approach of Tibshirani and Hastie (1987) and Fan and Gijbels (1996). The resulting 'local maximum likelihood approach to estimate the stochastic frontier' (LMLSF) does not require an *a priori* specification of the global frontier. Additionally, the approach is robust for unknown heteroskedasticity in both noise and inefficiency. Basically, the idea is to make the parameters of a parametric model dependent on the covariates via a process of localization. As such, no global restrictions are imposed on (1) the functional form of the frontier, (2) the distribution of inefficiency, and (3) the distribution of noise. In result, for each data point, the marginal frontier impact of inputs can be estimated. However, this comes at a cost as the localization can result in a global frontier which is non-monotone and non-convex.

Kumbhakar et al. (2007) have shown the value of the LMLSF approach in analyzing the cost function of a random sample of 500 U.S. commercial banks. Additionally, Kumbhakar and Tsionas (2008) have applied the approach to estimate stochastic cost frontier models for a sample of 3691 U.S. commercial banks, while Serra and Goodwin (2009) use the approach to compare efficiency ratings of organic and conventional arable crop farms in the Spanish region of Andalucía.

To our best knowledge, the LMLSF approach has never been used to estimate the production process of cognitive skills. Nevertheless, the LMLSF is well suited for educational settings. Firstly, there is no *a priori* information on the relationship between the educational inputs (such as instruction time, teacher experience and resources for care) and the educational attainments (i.e., test scores). Secondly, the LMLSF approach conveniently estimates the effectiveness of the inputs, which is often neglected in educational applications. The literature suggests that the total size of the education budget does not influence the educational attainments of students (Hanushek, 2003; Wößmann, 2003, 2005; Gundlach et al., 2001). However, it is worthwhile to examine for each educational input separately its effectiveness.

This paper contributes to the literature in three different aspects. Firstly, it indicates the value of semiparametric frontier approaches to study education as a complex production process in a noisy and heterogeneous setting. In a vast literature, education is considered as a production process where the student uses his/her own inputs as well as the school inputs to create educational output in a given institutional setting (e.g., Hanushek and Welch (2006) and Wößmann (2008) for reviews). Most education production studies do not allow for inefficiency and impose *a priori* a parametric functional form of the production process. Some exceptions are nonparametric frontier approaches, such as Grosskopf et al. (1997, 1999), Johnes (1996, 1993), Mancebon and Molinero (2000), Portela and Thanassoulis (2001), Thanassoulis and Dunstan (1994) and Cherchye et al. (2010), which estimate nonparametrically pupil inefficiency. However, the absence of information on the marginal impact of inputs is a large caveat of similar frontier approaches. Perelman and Santin (2008) propose a stochastic parametric distance function approach to estimate pupil efficiency and the marginal impact of pupil and school inputs. However, the global parametric assumptions on (1) the functional form of the frontier, and (2) the distribution of noise and inefficiency are restrictive in an educational setting. As there is no clear *a priori* information on the transformation of educational resources into educational attainments, it is difficult to justify *a priori* assumptions on the functional relationship between pupil guidance and educational outcomes. In addition, an educational setting is characterized by large heterogeneity between pupils - e.g. caused by their unobserved innate ability - and random noise - caused by the appearance of luck and measurement error in cognitive skills tests. For this, clearly, a semiparametic frontier approach is superior. The best suited methodology to examine the problem is the LMLSF approach, as this model has some significant advantages which are outlined above.

As a second contribution, this paper focuses on the marginal impact of pupil guidance on educational outcomes. As budgets are limited, resources should be spent as efficient (= doing the things right) and effective (= doing the right things) as possible. The same yields for resources spent on care (although some policy makers may suggest that more resources spent on care is always preferable).

Using the LMLSF model we examine whether students effectively benefit (in terms of higher output attainments) from resources spent on 'care'. Currently, evidence is coming from two sides. Firstly consider evidence coming from revealed policy in various industrialized countries. There seems to be a broad consensus among policy makers that students benefit from 'care' at school (i.e., psychological aid, pedagogical aid, social work, etc.). For example, in the United States, pupil guidance is considered as an effective instrument to reach the goals of the 'No Child Left Behind Act' (McGannon et al., 2005). Via the American School Counselling Association, substantial effort is made to standardize school counselling and make school counsellors responsible for demonstrating their effectiveness. In Hong Kong, in 2003-2004, over 96 percent of the primary schools reported to have guidance teams (Yuen et al., 2007). In Finland, pupil guidance is considered as a means to reach inclusive education (Halinen and Järvinen, 2008). In the Flemish community of Belgium, one of the main goals of the large efforts to improve collaboration between schools is to facilitate pupil guidance (Day et al., 2008). In this paper, we will consider the effectiveness of resources spent on care in the Dutch primary education for which we have a rich data set.[2]

Secondly, consider the sociological and psychological literature - reviewed in among others Whistin and Sexton (1998) and McGannon et al. (2005). This growing literature has assessed the role of pupil guidance in (1) closing the gap between disadvantaged and advantaged pupils, and (2) raising the education quality. By the use of randomized trials and quasi-experiments, the literature has shown that a broad range of school counselling programs often result in higher educational performance and higher well-being of the pupils. In contrast, the economic literature on education is silent on both the role and the effectiveness of pupil guidance in the production process of cognitive skills. According to the operational research literature, a micro-level study on the effectiveness of pupil and school inputs requires an approach that (1) allows for inefficiency, (2) does not impose restrictive assumptions on the functional relationship between inputs and educational output and (3) allows for the existing heterogeneity between pupils and noise that results in standardized testing. Following this strand, this paper tries to introduce pupil guidance in the economic literature on efficiency in schooling. We directly assess pupil guidance as a pupil input in the production process of cognitive skills.

As a third contribution, we examine the impact on the educational attainments of expe-

[2]This paper does not intent to describe the Dutch primary education system, see e.g., Luyten et al. (2009).

rience of the teacher and the time spent on math courses. In addition, we make a clear distinction between native and non-native students. As non-native students suffer from other difficulties at school than native students (e.g., different knowledge of the language, different home situation) we estimate the impact of 'care' on the production process separately for native and non-native students. Separating the two groups (cf. the frontier separation approach) controls for heterogeneity in family background.
The paper unfolds as follows. Section 2 describes the local maximum likelihood stochastic frontier estimation procedure and provides its practical computation. Section 3 describes the data and the issues at stake while Section 4 presents the results. Section 5 summarizes some results.

2 Local maximum likelihood stochastic frontier estimation

This section briefly reviews the estimation of a local maximum likelihood stochastic frontier (LMLSF). Full details can be found in Kumbhakar et al. (2007). Following Kumbhakar et al. (2007), we consider a set of i.i.d random variables (X_i, Y_i), for $i = 1, ..., n$, with input $X_i \in \Re^d$ and output $Y_i \in \Re^q$. The joint probability density function (pdf) of (X, Y) is decomposed in a marginal pdf for $X : pdf(x) = p(x)$ and a conditional pdf for Y given $X : pdf(y|x) = g(y, \theta(x))$, where $\theta(x) \in \Re^k$ is to be estimated and g is assumed to be known. The local maximum likelihood is based on a local parametric anchorage model. Typically, the frontier function $r(X)$ is introduced as in the parametric model of Aigner et al. (1977):

$$Y_i = r(X_i) - u_i + v_i \text{ , with } i = 1, ..., n \tag{1}$$

with input-output vector (X, Y) usually in log-scale, the inefficiency term u is specified to have a half normal distribution $(u|X = x \sim |N(0, \sigma_u^2(x)|)$, the error term v is normally distributed $(v|X = x \sim N(0, \sigma_v^2(x)))$ and u and v are independent conditionally on X.
The basic idea of the LMLSF approach is to use a local polynomial approximation to estimate the unknown 3-dimensional local parameter $\theta(x) = (r(x), \sigma_u^2(x), \sigma_v^2)^T$. To do so, the conditional log-likelihood is written as:

$$L(\theta) = \sum_{i=1}^{n} \log g(Y_i, \theta(X_i)). \tag{2}$$

The local approximation of this conditional log-likelihood function by the use of an mth order local polynomial fit is expressed as:

$$L_n(\theta_0, \theta_1, ..., \theta_m) = \sum_{i=1}^{n} \log g(Y_i, \theta_0 + \theta_1(X_i - x) + ... + \theta_m(X_i - x)^m)K_H(X_i - x), \tag{3}$$

where x is a fixed interior point in the support of the probability density function $p(x)$, $\theta_j = (\theta_{j1}, ..., \theta jk)^T$, $K_H(u) = |H|^{-1}(H^{-1}u)$, with K a multivariate kernel function and H a positive definite and symmetric bandwidth matrix.
The local polynomial estimator $\hat{\theta}(x)$ is given by $\hat{\theta}(x) = \hat{\theta}_0(x)$ where

$$(\hat{\theta}_0(x), ..., \hat{\theta}_m(x)) = \text{arg max}_{\theta_0,...,\theta_m} L_n(\theta_0, ..., \theta_m). \tag{4}$$

A higher order of polynomials entails a higher dimension of unknown parameters. Estimation becomes more cumbersome and less accurate in small sample. As shown in Kumbhakar et al. (2007), a local linear fit suffices for a flexible estimation of the frontier and marginal frontier impact of inputs. Therefore, we approximate the conditional log-likelihood function by:

$$L_n(\theta_0, \Theta_1) = \sum_{i=1}^{n} \log g(Y_i, \theta_0 + \Theta_1(X_i - x))K_H(X_i - x) \tag{5}$$

with θ_0 a 3×1 vector, Θ_1 a $3 \times d$ matrix.
We estimate the fit of the frontier (θ_0), the marginal impact of the inputs on the frontier (θ_1), the variation of respectively inefficiency (σ^2_{0u}) and noise (σ^2_{0v}), the marginal impact of the inputs on the variation of respectively inefficiency (σ^2_{1u}) and noise (σ^2_{1v}). By this, we have observation-specific estimates of the marginal impact of the inputs on the frontier while allowing for heterogeneity in inefficiency and random noise. Thus, in contrast to parametric stochastic frontier approaches, no *a priori* specification of the global frontier and no global assumptions on the distribution of inefficiency and random noise are required. In contrast to traditional DEA approaches, (1) inefficiency is separated from random noise, (2) results are robust for outliers because random noise is allowed, (3) observation-specific marginal impacts of inputs on the frontier are estimated. In sum, this approach combines the merits of DEA and SFA by estimating the frontier and marginal frontier impact of inputs with only mild assumptions in a stochastic and heteroscedastic setting (for an extensive discussion, see Kumbhakar et al., 2007).

3 Do students benefit from care?

Different from about 10 years ago, industrialized countries pay a large attention to individual care for students. This student care is provided in terms of psychological help, logopaedics, physiotherapy, medical care, social workers, or individual training on specific subjects (as languages or maths). In the end, student care aims at improving the student well-being such that he/she obtains improved educational attainments. Although the literature has already examined the impact of student care, this research is the first to look at the marginal impact of care on student performance while allowing for inefficiency.

We analyze the impact of student care for a large sample of Dutch primary school students as the impact of student care may be particularly revealed at the primary education level. Indeed, within Dutch primary education large resources are spent on individual training on specific subjects and on individual guidance to improve the well-being of the pupil. As such, it is likely that the effect of student care is more clearly detected for primary school pupils than for secondary education. To examine the research question we use the 2002-2003 data from the so-called Prima-cohort (which follows a cohort of pupils in Dutch primary education).

The LMLSF model requires the specification of input and output variables, which we deduced from the Prima-cohort research. As we are interested in the impact of care on the performance of students, we proxy the educational attainments of students by the test scores on math.[3] In the Netherlands, students take standardized tests from the central government. As such, the scores are perfectly comparable across schools and regions. Summary statistics are presented in Table 1. While the test scores are uniform in the Netherlands, there might arise some heterogeneity across schools in instruction time on the particular subjects. Therefore, we model instruction time on math (expressed in minutes) as an input variable. As teachers with more experience, may teach differently and, as such, obtain higher educational attainments with their students, we include teacher experience as a second input variable. A third input variable aggregates the total number of counselling per student at the school. This proxy for 'student care' includes the time a social worker, psychologist, educator, nurse, or a speech therapist attend the school.

To control for family background, we examine the effectiveness of the resources (the inputs) on two groups of pupils, i.e. native and non-native students, which are in principle benefiting from similar school resources as they take the same courses in the same classes, but have different socio-economic and cultural inputs.[4] The literature discussed extensively the importance of ethnicity on test outcomes. As in most western countries, in the Netherlands, non-native pupils have on average a low socio-economic status and low educational performance (OECD, 2006). It is therefore interesting to examine the effectiveness of the resources on the educational attainments of the two groups.[5]

As presented in Figure 1, resources spent on student care are heterogeneous among schools. To obtain some insights on which of the care elements has an effective impact on the edu-

[3]The test score on maths is preferred on the test score on other subjects as it is less (but still) influenced by knowledge of the test language.

[4]As our robustness checks did not find any effects of the average number of non-native pupils in a class, we do not include the peer effects of migration status in the model.

[5]In the DEA literature, this approach of separating the samples corresponds to the popular 'frontier separation approach'.

cational attainments, in a second phase, we distinguish care by social workers and care by psychologists and educators.[6] To allow for multiplicative effects, all input and output variables are expressed in their natural logarithm. To avoid scale problems in the bandwidth selection, inputs are standardized. The final sample, which is obtained from the 2002-2003 Prima-cohort, consists of 1,034 pupils in 25 different schools. As in the Netherlands about all primary school pupils attend the nearest primary school, we do not expect any selection bias effects in our sample.

To obtain insights in the marginal impact of (1) instruction time, (2) teacher experience and (3) student care, on educational attainments, we estimate the model by the outlined LMLSF approach. Thanks to two issues, the LMLSF model is well suited for this particular application. Firstly, as a researcher, we do not have any information on the relationship between inputs and outputs. Therefore, any *a priori* assumption on the production technology (i.e., the transformation of inputs into outputs) will potentially lead to biased estimates. Secondly, the LMLSF model allows us to conveniently estimate the effectiveness of resources. Often, the literature only estimates the efficiency (i.e., doing the things right) of observations, while ignoring the effectiveness (i.e., doing the right things). By analyzing the marginal impact on the frontier, we can proxy the effectiveness of the resources.

The results are presented in Figure 2 and Table 3. Visualization of minimization of the cross-validation function for an appropriate grid of bandwidths is given in Figure 5 in appendix. The chosen bandwidth is given in Table 2 in appendix. We consider the impact of a variable as significantly (un)favorable if both the first and second quartile of the observations experience a positive (negative) impact (see Table 3). From Figure 2 we can deduce that both instruction time and experience of the teacher have a significant impact on educational attainments of native and non-native students. Both experienced teachers and a longer instruction time lead to higher test scores. Nevertheless, the standard deviation is larger for non-native students such that the significance level of the effectiveness would be lower (probably due to the fewer number of non-native students in the sample).[7]

As student care is still a wide variable, in Figures 3, 4 and Table 4, we decompose the care component into aid by social workers on the one hand and by psychologists and educators on the other. Again, visualization of minimization of the cross-validation function for an appropriate grid of bandwidths is given in Figure 6 and Figure 7 in appendix. The chosen bandwidth is given in Table 2 in appendix. Firstly, consider the effectiveness of both types

[6]Due to data constraints, the analysis is limited to these two components of care.

[7]The traditional frontier separation approach suffers from a similar sample size bias in that groups with lower sample size have by construction a higher average efficiency level.

of care on native students. The results are presented in Figure 3. The left hand side of Figure 3 presents the effectiveness of the resources if 'care' is limited to only psychological and educator help. The results reveal that this type of care effectively improves the student test scores. As revealed from the right hand side of the figure, social workers seem ineffective in increasing the test scores. This might be due to two issues: (1) social workers operate more as an advisory team at the level of the family, while psychologists and educators work more directly with the pupils, and as such, their influence on the test scores turns out to be larger. (2) As there are less schools which employ social workers, there might arise some selection bias in that only schools with significant problems (and hence lower test scores) hire social workers. Secondly, consider the detailed impact of care on non-native students. Table 4 reveals that, while teacher experience and instruction time is still significantly favorable to education attainments of non-native students, the impact of social workers is non-significantly different from 0. It seems that, for non-native students, resources spent on social work are not effective.

In sum, our results reveal that care works effectively at school for both native and non-native students. However, if one disentangles care into two popular subgroups (i.e., aid by psychologists and educators and aid by social workers), the results suggest that only the more individualized psychological and educator help improve significantly the educational attainments.

Table 1: Summary statistics

All students	Average	St. Dev	Minimum	First quartile	Median	Third quartile	Maximum
Output							
Student attainment on maths	43.32	19.13	6.00	30.00	44.00	53.00	95.00
Input							
Time for student counselling per student	0.14	0.09	0.00	0.08	0.13	0.17	0.36
Time spent on instructing math	238.60	44.98	110.00	220.00	225.00	270.00	500.00
Experience teacher	15.00	10.65	1.00	5.00	12.00	23.00	36.00
Time for educator and psychologist per student	0.08	0.06	0.00	0.04	0.05	0.10	0.24
Time for social worker per student	0.04	0.03	0.00	0.03	0.03	0.05	0.19
Ethnicity students							
Number of natives	763						
Number of migrants	271						

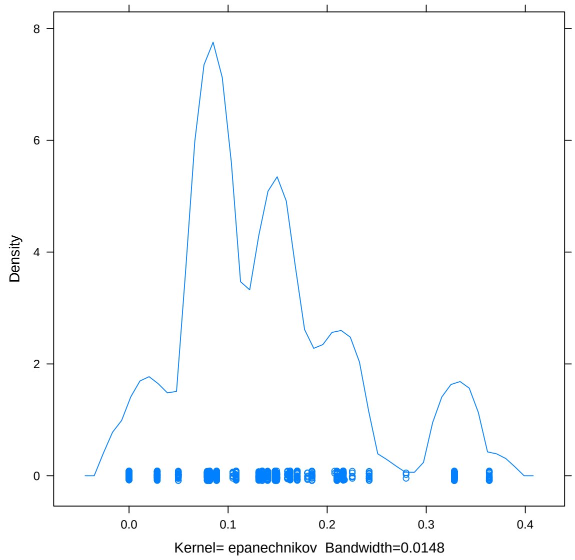

Figure 1: Kernel density of care per student, rug plot of values is shown along the bottom of the plot

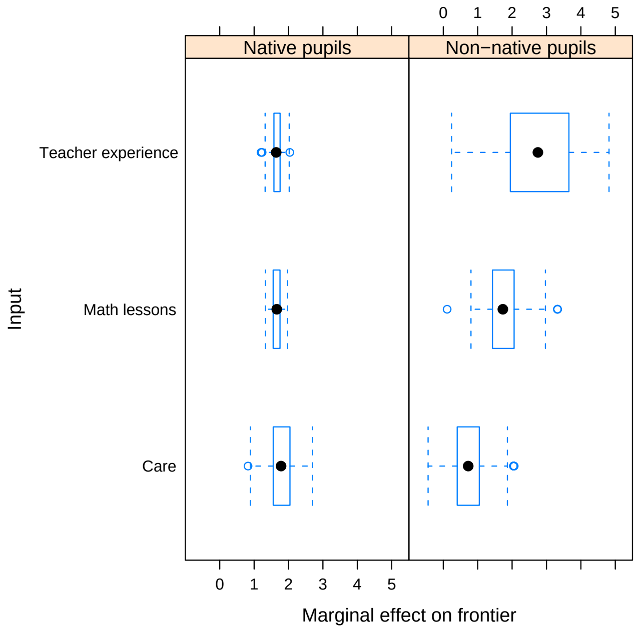

Figure 2: Marginal frontier effects of inputs

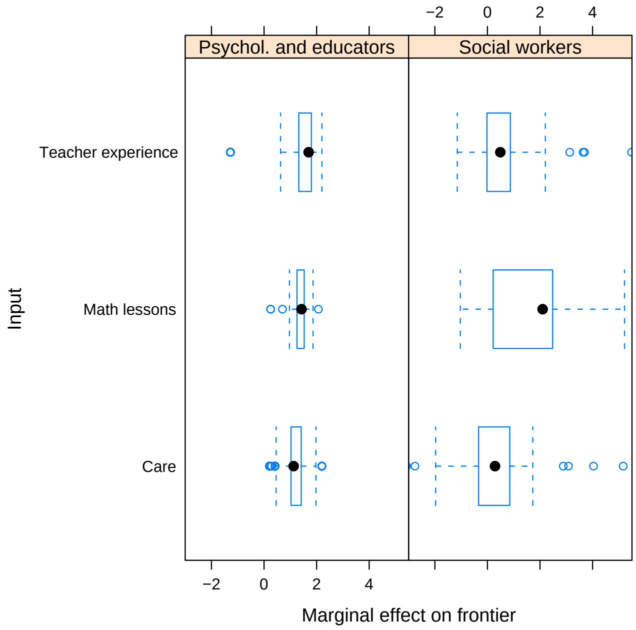

Figure 3: Effectiveness of inputs on performance native students

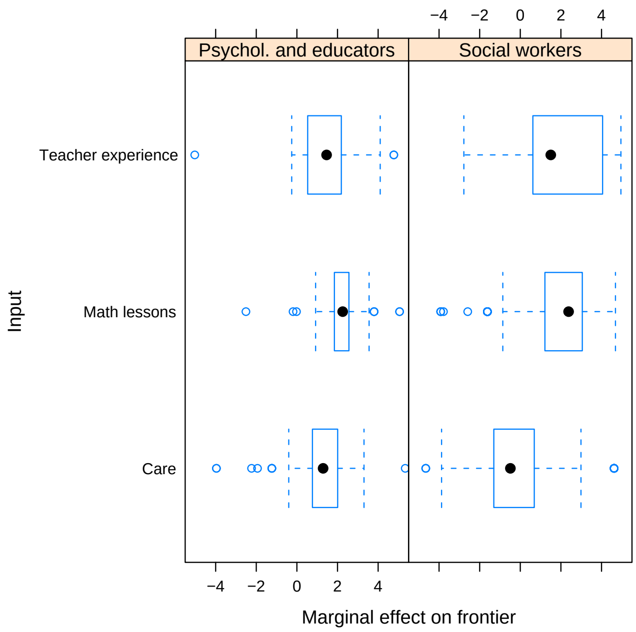

Figure 4: Effectiveness of inputs on performance non-native students

4 Conclusion

While the efficiency of observations received a significant attention in the literature, the effectiveness of resources is less an issue (yet). Nevertheless, the scarce resources should be spent as effectively as possible. Using a local maximum likelihood estimation of the stochastic frontier (LMLSF), this paper estimates the effectiveness of student care for primary education students. We particularly examined for both native and non-native students (i.e., by estimating the LMLSF-model on both subgroups) the effectives of instruction units, teacher experience and care (in terms of care by psychologists and social workers).
The results reveal that while care in total is effective and favorable to student attainments, the individual components are not undoubtly. Psychologists turn out to have a significant impact on both natives' and non-natives' educational attainments. On the contrary, social workers do only have an effective impact on test scores of native students.
This study is obviously only a first and exploratory research, and not a full in-depth analysis of student care. The paper attempts to provide a framework to (1) show how the effectiveness of resources can be nonparametrically examined while accounting for other influences, and (2) estimate the added value of student care on educational attainments. Further research could explore the impact of student care while controlling for a broader range of background characteristics.

5 Appendix

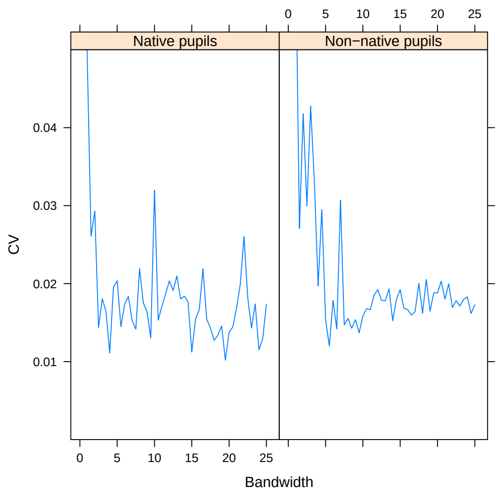

Figure 5: Cross Validation: native and non-native pupils

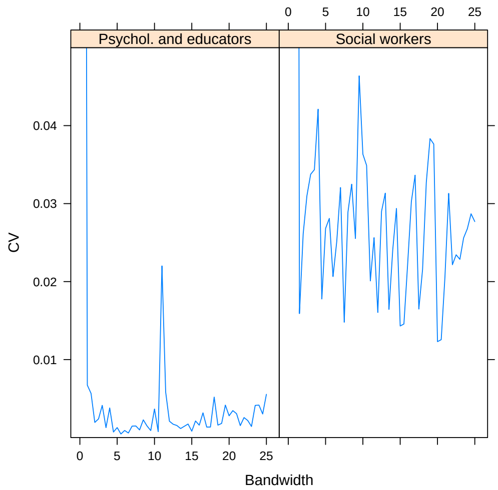

Figure 6: Cross validation: native pupils

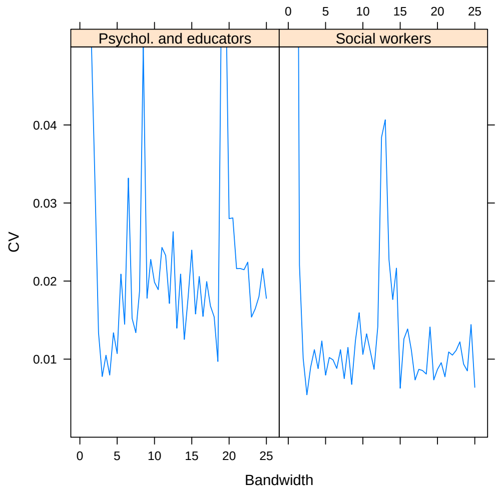

Figure 7: Cross validation: non-native pupils

Table 2: Bandwidth

Model	h_{base}	h_1	h_2	h_3
Native-pupils (care = time for student counselling)	19.5	0.252	0.261	0.256
Native pupils (care = time for psychologists and educators)	20	0.257	0.267	0.262
Native pupils (care = time for social workers)	5.5	0.069	0.074	0.072
Non-native pupils (care = time for student counselling)	3	0.089	0.089	0.089
Non-native pupils (care = time for psychologists and educators)	5.5	0.047	0.048	0.049
Non-native pupils (care = time for social workers)	2.5	0.040	0.040	0.041

Table 3: Summary statistics

Native pupils, care = time for student counselling						
	care	time	experience	$\hat{\sigma}_u^2$	$\hat{\sigma}_v^2$	$\hat{\lambda}$
Minimum	0.823	1.327	1.201	0.397	0.014	2.806
First quartile	1.555	1.553	1.576	0.513	0.023	4.132
Medium	1.783	1.659	1.641	0.534	0.029	4.382
Mean	1.786	1.651	1.650	0.601	0.030	4.596
Third quartile	2.042	1.753	1.755	0.661	0.035	4.874
Maximum	2.693	1.973	2.037	1.126	0.073	8.861
Non-native pupils, care = time for student counselling						
	care	time	experience	$\hat{\sigma}_u^2$	$\hat{\sigma}_v^2$	$\hat{\lambda}$
Minimum	-0.442	0.111	0.242	0.164	0.002	1.050
First quartile	0.404	1.430	1.948	0.383	0.016	2.705
Medium	0.724	1.731	2.750	0.660	0.027	4.518
Mean	0.750	1.787	2.757	0.603	0.045	5.246
Third Quartile	1.047	2.058	3.652	0.748	0.059	6.951
Maximum	2.061	3.320	4.818	1.122	0.155	24.315

Table 4: Summary statistics, care decomposed

Native pupils, care = time for psychologist and educator						
	psych.	time	experience	$\hat{\sigma}_u^2$	$\hat{\sigma}_v^2$	$\hat{\lambda}$
Minimum	0.205	0.251	-1.279	0.376	0.005	1.514
First quartile	1.025	1.253	1.322	0.501	0.030	3.362
Medium	1.127	1.426	1.696	0.544	0.038	3.661
Mean	1.199	1.404	1.517	0.577	0.041	4.002
Third quartile	1.414	1.528	1.804	0.639	0.047	4.297
Maximum	2.200	2.069	2.200	1.183	0.179	11.340
Native pupils, care = time for social workers						
	soc.w.	time	experience	$\hat{\sigma}_u^2$	$\hat{\sigma}_v^2$	$\hat{\lambda}$
Minimum	-3.131	-1.032	-1.148	0.000	0.000	0.027
First quartile	-0.330	0.223	-0.013	0.516	0.000	10.794
Median	0.288	2.100	0.491	0.604	0.000	34.394
Mean	1.309	1.933	0.855	0.642	0.016	1.289e+05
Third quartile	0.842	2.480	0.867	0.706	0.006	6.823e+02
Maximum	15.486	8.014	6.660	1.911	0.588	7.174e+06
Non-native pupils, care = time for psychologist and educator						
	psych.	time	experience	$\hat{\sigma}_u^2$	$\hat{\sigma}_v^2$	$\hat{\lambda}$
Minimum	-160.687	-2.509	-5.028	0.000	0.000	0.000
First quartile	0.766	1.847	0.532	0.450	0.035	3.016
Medium	1.291	2.255	1.462	0.586	0.047	3.539
Mean	0.757	2.394	1.806	0.591	0.051	4.015
Third quartile	2.008	2.562	2.188	0.675	0.051	3.949
Maximum	5.335	62.935	103.558	2.034	0.562	21.743
Non-native pupils, care = time for social workers						
	soc.w.	time	experience	$\hat{\sigma}_u^2$	$\hat{\sigma}_v^2$	$\hat{\lambda}$
Minimum	-841.227	-3.918	-2.779	0.000	0.000	0.004
First quartile	-1.304	1.213	0.620	0.546	0.005	4.540
Median	-0.488	2.379	1.502	0.722	0.011	8.370
Mean	-3.140	2.168	2.108	0.658	0.023	1.248e+30
Third quartile	0.688	3.054	4.053	0.753	0.037	11.769
Maximum	4.618	10.336	93.528	1.276	0.472	3.506e+32

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