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“Measuring efficiency in education: an analysis of different approaches for incorporating non-discretionary inputs”

Summary

Measuring efficiency in the education sector is a highly complex task. One of the reasons is that the main resource of schools (the type of students they have) lie outside of their control, which means that it must be treated differently to other factors in analysis. This study examines the different options available in the literature for incorporating non-controllable inputs in a DEA analysis in order to determine the most appropriate model for evaluating schools. Our empirical study presents the results obtained using the model proposed by Fried et. al (1999), though we use bootstrap techniques to avoid problems of bias in the estimations.

Key words: DEA, Efficiency, Exogenous Factors, Bootstrap

1. INTRODUCTION

The special attention that both public authorities and the scientific community have always paid to the educational sector makes good sense if we remember that there is a strong correlation between the quality of education, measured through the results obtained in international tests, and countries' economic growth (Hanushek and Kimko, 2000, or, Barro, 2001).

A good part of research activity in recent years has been directed towards analysing the behaviour of schools by trying to measure their efficiency levels, making it necessary to relate results with resources. The analysis of efficiency in the educational field is more complex than in other production sectors for various reasons. These include the difficulty of measuring output, medium term effects or the fact that the production function is unknown. Since the publication of the Coleman Report (1966), it has also been recognized that the effects of certain exogenous factors on output, such as the pupils' socio-economic characteristics or their abilities, may be greater than others typical of the educational process (teachers, cost per student, class sizes, etc.) If we take into account that these factors are outside the control of schools the complicated task of evaluating the efficiency of their performance becomes more difficult.

A review of the literature in this area enables us to verify that, in addition to the accepted significance of these exogenous factors, there are many different options for including them in evaluations. While the first studies considered controllable and non-controllable inputs in the same way (Bessent et. al, 1982), more recent studies include both inputs together in a single stage, though treating them differently (Ruggiero, 1998). The evaluation process in other studies comprises several stages with the objective of treating the special nature of these factors in an appropriate way (Ray, 1991; McCarty and Yaisawarng, 1993; Simar and Wilson, 2003). Within the multi-stage options, there are theoretical

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3 propositions that have not yet been applied in the educational field (Fried
4 et. al, 1999 or Fried et. al 2002).
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9 In this context it seems appropriate to question the suitability of the
10 different models. There are some interesting earlier studies into this issue
11 which compare the results obtained from applying some of the proposed
12 models to a specific sample (Worthington and Dollery, 2002). In this study,
13 in addition to considering new options, we concentrate on their
14 advantages and disadvantages from both a methodological and practical
15 perspective. Through this analysis our aim is to point out the main aspects
16 of each technique that must be taken into account when it comes to
17 deciding which option is the most appropriate to deal with this type of
18 variables in an empirical study.
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28 In order to illustrate this issue, we analyse a particular case.
29 According to the characteristics of the data set and the preliminary results
30 obtained in a standard DEA, an extension of the model proposed by Fried
31 et. al (1999) is used in order to discount the effect of non-controllable
32 inputs. This model has not been applied before to the measurement of
33 efficiency in schools.
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41 To this end, our article is organised as follows. Section 2 is a brief
42 synopsis of some important issues concerning the measurement of
43 efficiency in education and Data Envelopment Analysis (DEA). Section 3
44 presents and analyses the different options for incorporating non-
45 discretionary inputs into the measurement of efficiency. In section 4, we
46 analyse the performance of a group of Spanish high schools using DEA
47 and present the main results obtained by applying the most appropriate
48 approach (from a theoretical and practical point of view) for these data in
49 order to include non-discretionary inputs in the assessment. Section 5
50 shows the main conclusions.
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2. THE MEASUREMENT OF EFFICIENCY IN THE EDUCATIONAL SECTOR

Despite the great number of papers published in recent decades about the assessment of efficiency in education, the production function in the sector is still unknown (Engert, 1996). There are several explanations for this. Education is not an instantaneous thing but generates its effects in the medium term; the output, which is multi-dimensional and difficult to measure, is the consequence of a complex process influenced by many factors, some outside the control of the productive units. This makes it extraordinarily difficult to define a general educational production function that accurately includes all relevant aspects of the school production process and, consequently, making it possible to measure efficiency through a simple comparison between real results and those which could potentially be achieved (Hanushek, 1986).

The main interest of researchers in this area had been trying to define and measure the school output, identifying the factors that influence it most and linking the former with the latter while respecting the sector's special characteristics.

The measurement of educational output is usually restricted to those aspects that are relatively easy to measure and are directly related to the basic objectives of the relevant educational level. In the case of secondary education, it is usual to use the results achieved by students in an homogeneous test for all schools at the end of the school year.

With respect to inputs, despite the difficulties presented by the specification of an educational production function, there is empirical evidence to identify the factors that have a greater influence on school output. The Coleman Report (1966), which analysed the behaviour of a broad sample of non-university educational schools and is one of the most influential studies in the literature, concluded that the characteristics of pupils – a variable on which the centres in principle do not exercise any

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3 control – affected performance more than the typical resources of schools
4 such as the number of teachers, class sizes or the school costs.
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9 The publication of this report led to a wide-ranging debate between
10 those who hold that these factors have no influence on educational results
11 (Hanushek, 1986) and those who believe that spending more on education
12 produces better results (Pritchett and Filmer, 1999). In any case, a study
13 which aims to measure the productive efficiency of a group of schools
14 must also consider these productive factors, since in the concept of
15 technical efficiency is implicit the idea of how well resources are used.
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23 The case of exogenous or environmental variables, which are
24 common in other productive sectors, is different. Their influence on school
25 output has been widely confirmed by empirical evidence and it is usually
26 associated with a specific producer characteristic which may affect results
27 (Pedraja and Salinas, 1996). Examples in the educational sector are the
28 type of ownership of the schools (public or private) or their location (urban
29 or rural). In these circumstances, the usual solution is to group units and
30 compare them with those operating in a similar environment.
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39 On the other hand, the representative variables of pupil
40 characteristics, which are also sometimes considered as exogenous, are
41 inputs which have a direct effect on the productive process and influence
42 the results. These inputs, which the units cannot control (non-controllable
43 inputs), should be considered in the efficiency evaluation so that those for
44 which the educational centres are responsible can be calculated.
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51 However, public data about these variables are not usually
52 available, thus simple proxies for them are used in many studies¹. One
53 way to overcome these limitations, although costly and therefore
54 infrequently used, is to conduct surveys of pupils in order to obtain
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¹ Some examples are the studies by Bessent et. al (1982) or Thanassoulis and Dunstan (1994), which approximate the economic situation of families by using the percentage of pupils entitled to discounted meals.

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3 information on the factors identified in the literature as the most influential:
4 the socio-economic and family environment, the innate ability of the
5 students and the characteristics of their class mates (peer group effect).
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10 With respect to the technique used to measure the relative
11 efficiency of schools, two main alternatives can be considered: parametric
12 and non-parametric methods². In the literature, on the one hand, some
13 studies comparing efficiency scores generated by both techniques for a
14 specific sample (Bates, 1997; Chakraborty et. al, 2001; Mizala et. al, 2002)
15 may be found. On the other, there are studies using Monte Carlo
16 experiments where the underlying production technology is known (Yu,
17 1998). Nevertheless, most authors use non-parametric approximations
18 and, specifically, Data Envelopment Analysis (DEA)³. This choice is
19 based, amongst other reasons, on its great flexibility, which makes it
20 particularly suitable in an area such as education where the production
21 function is unknown, and on its ability to adapt to processes involving not
22 only a range of inputs but also a series of intermediate outputs, rather than
23 a single final input⁴. Moreover, in recent years different methods have
24 been developed to incorporate in the technique the fact that there are non-
25 controllable inputs when efficiency scores are calculated, which is of
26 particular interest in the educational sector.
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42 DEA, introduced by Charnes, Cooper and Rhodes (1978), is
43 characterised by the fact that it does not impose a specific functional form
44 on the production function, but rather establishes certain assumptions
45 about the properties of technology which allow the definition of the set of
46 feasible productive processes whose frontier envelops the observed data.
47 The standard formulation of the programme can take several forms
48 according to different criteria, so it can be oriented to reduce input values
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56 ² See Lovell (1993) or Coelli et. al (1998) for a detailed discussion on the methods for
57 analyzing technical efficiency.

58 ³ Charnes et. al (1981), Bessent et. al (1982), Smith and Mayston (1987), Thanassouliss
59 and Dunstan (1994), Chalos (1997) or Thanassouliss and Portela (2002) are some
60 examples.

or increase output values. It can also be presented as a fractional programme (the original model), linear or dual. However, they all share the same approach: the efficiency of each unit depends on the ability of each producer to improve their results or reduce the consumption of resources while being subject to certain restrictions that reflect the activity of other producers.

From our perspective, if the aim is to evaluate the behaviour of a group of units, with a restricted budget, seeking to obtain the best possible results, it is advisable to use an output-orientated programme. In terms of its formulation, the dual programme is the most common option⁵:

$$\begin{aligned}
 \text{Max} \quad & \phi + \varepsilon \sum_{i=1}^m s_i^- + \sum_{r=1}^s s_r^+ \\
 \text{s.a.} \quad & \sum_{j=1}^n x_{ij} \lambda_j + s_i^- = x_{i0} \quad i = 1, 2, \dots, m \\
 & \sum_{j=1}^n y_{rj} \lambda_j - s_r^+ = \phi y_{r0} \quad r = 1, 2, \dots, s \\
 & \lambda_j \geq 0; s_r^+ \geq 0; s_i^- \geq 0 \quad j = 1, 2, \dots, n
 \end{aligned}$$

where ϕ_0 is the efficiency score, ε is an infinitesimal non-Archimedean, λ_i are the weightings and s_i^- and s_r^+ are the inputs slacks and outputs slacks respectively. If the score is equals one the producer is relatively efficient compared to other units. If the score is lower than one, the unit evaluated is inefficient as the sample contains other units which perform better.

This formulation of the programme is particularly attractive since, in addition to allocating an efficiency score to each unit, it allows possible

⁴ Seiford and Thrall (1990) consider that using DEA is preferable to any other type of analysis when the objective is to measure the efficiency of a group of organisations producing various outputs.

⁵ The model defined corresponds with the original version of DEA proposed by Charnes, Cooper and Rodhes (1978), which assumes a productive technology characterised by an assumption of constant scale returns. This highly restrictive assumption was later relaxed

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3 additional reductions in inputs or potential increases in outputs to be
4 detected in specific cases, using the slacks estimated for each variable.
5 This interesting information is complementary to that offered by the
6 efficiency score and may be extremely useful when it comes to identifying
7 the source of possible producer inefficiencies.
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12 13 14 **2. DIFFERENT OPTIONS FOR INCORPORATING NON-** 15 **CONTROLLABLE INPUTS: ADVANTAGES AND DISADVANTAGES.** 16 17

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19 A review of different options in the literature in order to incorporate
20 exogenous factors in the assessment of efficiency allows us to make an
21 initial distinction between methodologies using one and several stages. In
22 one stage models, non-controllable inputs are included from the outset in
23 the calculation of efficiencies using a DEA alone. Multi-stage models use a
24 DEA to estimate efficiency scores in an initial evaluation without including
25 non-discretionary inputs and then subsequently correct them to take
26 account of the effects of such inputs. This correction can be applied
27 directly to the scores or by modifying the original values of the variables,
28 leading to new options within the second group.
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38 From this perspective it seems sensible to seek a guide for
39 selecting the most appropriate options. We will therefore examine the
40 principal advantages and disadvantages of the options in the literature⁶
41 combining a theoretical perspective with a more practical view according
42 to the objective of the analysis and the characteristics of the available data
43 set.
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50 **3.1. One stage models** 51 52 53 54 55 56 57

58 in the study by Banker, Charnes y Cooper (1984) with the introduction of a new restriction
59 in the programme to allow variable scale returns: $\sum \lambda_j = 1$.

60 ⁶ This analysis sets aside other methods which try to explain possible producer
inefficiencies by the influence of ambiental or environmental variables such as the models
of Charnes et. al (1981), Pastor (1994) or Daraio et. al (2005).

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3 One stage models (Banker and Morey, 1986; Golany and Roll,
4 1993; and Ruggiero, 1998) are the most frequently used option⁷. These
5 models modify the restrictions of the standard DEA programme by
6 incorporating the uncontrollable nature of some of the inputs used. With
7 this modification, if the model is oriented to minimise inputs the
8 equiproportional reduction of the entire input vector is not pursued, but
9 only the subvector formed by controllable inputs.
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17 The principal advantage is its lack of complexity as it simplifies the
18 calculation of efficiency scores by incorporating all the relevant variables in
19 a single DEA. However, this option presents some methodological
20 problems. The first of these is that it is limited to an input-oriented
21 approach when, if we are trying to evaluate the performance of the
22 schools, an output-oriented approach would be more recommendable.
23 Moreover, with this approach all the inputs are fixed and it is not possible
24 to treat those outside the schools' control in a differentiated manner. The
25 second issue is that the efficient units are the same as those which would
26 be obtained by using a DEA in which all inputs were controllable by the
27 units. This happens because the frontier is the same in both cases and,
28 consequently, only the scores of the inefficient units are modified. The
29 third problem, which arises from the flexibility of the technique itself, is that
30 as the number of variables increases (through the introduction of
31 exogenous variables), the opportunities for a unit to become classified as
32 efficient increase automatically (Nunamaker, 1985). These limitations lead
33 us to examine the opportunities offered by multi-stage models.
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49 **3.2. Multi-stage models**

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52 Although these models have been criticised for not explicitly
53 including the effects of exogenous factors in the first stage, the fact is that
54 they do consider these effects implicitly in estimating efficiency scores.
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60 ⁷ Most of computer programmes specifically developed for DEA allow non-controllable inputs to be included automatically using this option. For a review of DEA computer programmes in the market, see Barr (2004).

The key is to calculate and discount correctly the effect of these factors to obtain final efficiency scores which reflect solely the performance of the units.

In this respect, two alternative methods may be identified: a direct adjustment of the initial efficiency scores themselves by using econometric techniques (*second stage models*), or an indirect adjustment by correcting variables (inputs/outputs), according to how they are affected by non-discretionary inputs, and applying a new DEA to the adjusted values after that (*adjusted value models*).

3.2.1. Second stage models

These models, usually known in the literature as *regression or second stage analyses*, consider non-controllable inputs (Z_j) as explanatory variables in a regression where the dependent variable is the initial efficiency score (θ_j)⁸. Once $\hat{\beta}_j$ are estimated, the initial scores are corrected according to the values of exogenous factors for each unit.

$$\theta_j = f(Z_j, \beta_j) + u_j$$

This adjustment can be made directly through the predicted values (McCarty and Yaisawarng, 1993) or following the technique proposed by Greene (1980) to avoid any unit having a lower estimated score after the correction (Noulas and Ketkar, 1998)⁹.

Its main advantage compared to other multi-stage models is its simplicity as the adjustments are performed directly on the efficiency scores obtained in the first stage. Nevertheless, this fact introduces a first limitation as the correction only takes into account the radial component of

⁸ While some studies use ordinary least squares (Ray, 1991), others use a *Tobit* (Kirjavainen and Loikkanen, 1998) because the efficiency scores are censored.

⁹ This mechanism consist of adding the largest positive residual from all the residuals to the predicted value to get the adjusted efficiency.

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3 inefficiency and not the possible inefficiencies derived from the existence
4 of slacks.
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9 Another limitation of a practical nature is that it can only be applied
10 if there is a significant relationship between the efficiency scores and
11 exogenous variables. Many studies assume, erroneously, that if the output
12 depends on uncontrollable outputs, there must be a significant relationship
13 between these factors and the efficiency score. However, this assumption
14 does not generally turn out to be correct, as efficiency depends on several
15 factors. As a consequence, the use of this model is conditional upon there
16 being a significant relationship between both variables.
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25 A fundamental criticism of these models is that standard
26 approaches to statistical inference in the context of limited dependent
27 variable models are invalid. This is due to the existence of correlation
28 among efficiency scores estimated in the first stage, since they are
29 estimated from data of all the units making up the sample (Xue and
30 Parker, 1999). However, this problem can be overcome by using *bootstrap*
31 techniques (Simar and Wilson, 2003)¹⁰. In particular, these authors have
32 developed two procedures (algorithms) for the second stage of production
33 efficiency analysis that allow for valid statistical inference¹¹. In fact, some
34 of the most recent papers in the education field apply these techniques to
35 include non-discretionary inputs in the measurement of technical efficiency
36 of units¹².
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48 These proposals are very attractive if the objective is to find
49 whether the sign is positive or negative and how much effect exogenous
50 factors have on efficiency indicators. However, we should remember that
51 with adjustments made using this option, scores higher than one (or lower
52 with an input orientation) may be obtained for all the units comprising the
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58 ¹⁰ The idea of applying bootstrapping techniques in measuring efficiency was already
59 suggested by Simar and Wilson (1998) and also applied by González and Miles (2002)
60 for two Spanish public services.

¹¹ The analytical expression of these algorithms are set out in Simar and Wilson (2003).

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3 sample¹³. This fact, which is explained by the zero sum criterion used in
4 the estimation of regressions, makes it impossible to construct a
5 production frontier and, consequently, difficult to establish production
6 objectives for the units from the set of reference (efficient) units.
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10 11 12 **3.2.2. Adjusted value models** 13

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15 In addition to regression or second stage models, the literature
16 offers other more complicated multi-stage applications, based on using the
17 total slacks (radial and non-radial components) obtained in the first stage.
18 The objective of these models is to identify the part of the slacks which is
19 explained by the effect of non-discretionary inputs and the part associated
20 with producers' own technical inefficiency. This decomposition means that
21 adjustments can be made to the values of variables (controllable inputs
22 and outputs) allowing the effect of exogenous factors to be discounted.
23 The last stage, which is the same in all models, consists in running a new
24 DEA incorporating the corrected values of variables according to non-
25 controllable inputs attributed to each unit. The new estimated scores
26 establish exclusively the efficiency level at which each producer operates.
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39 Within these models, the available options are differentiated by the
40 technique employed in breaking down the different factors that comprise
41 the slacks. The three stage model (Fried and Lovell, 1996) chooses a
42 DEA, the four stage model (Fried et. al, 1999) uses censored regressions
43 and the model proposed by Fried et. al (2002) opts for stochastic frontier
44 regressions.
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50 51 *a) Three stage model with DEA (Fried and Lovell, 1996)* 52

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54 The mechanism used for the discomposition of different factors is a
55 DEA which incorporates slacks as controllable inputs and non-controllable
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59 ¹² Oliveira and Santos (2005) use the first algorithm while Afonso and St. Aubyn (2005)
60 applies the second one to correct the scores obtained in first stage.

inputs as outputs. This introduces a problem of minimising inputs (slacks) subject to the value of the outputs (non-controllable inputs). In other words, the aim is to determine the extent to which the former can be reduced while taking the value of the latter to be fixed.

$$\begin{aligned}
 & \min \quad \beta_0 \\
 & \text{s.a.} \quad \sum_{i=1}^I \lambda_i x_{fi} - s^{-} = x_{f0} \\
 & \quad \quad \sum_{i=1}^I \lambda_i [(1-\theta_0)x_d + s_d^+] + s^{+} = \beta_0 [(1-\theta_0)x_d + s_d^+]_0 \\
 & \quad \quad \sum_{i=1}^I \lambda_i = 1 \\
 & \quad \quad \lambda_i, s_d^+, s^{-} \geq 0
 \end{aligned}$$

where the total slack detected in the first stage for each producer in the variable x_d is given by the expression: $[(1-\theta_0)x_d + s_d^+]_0$. As a result of this process the attainable target is obtained for each unit, taking account of how many non-discretionary inputs it has. These targets make it possible to identify what part of the slacks is explained by the influence of external effects, $\beta_0 [(1-\theta_0)x_d + s_d^+]_0$, and what is due to inefficiency, $(1-\beta_0)[(1-\theta_0)x_d + s_d^+]_0$. The values of inputs and outputs can be corrected following the original model or the alternative option proposed by Muñiz (2002).

Its principal advantage is the use of non-parametrical techniques in all stages of the analysis, which is very useful not only where there is ignorance about the productive process in sectors such as education, but also to overcome problems of bias that characterise the estimation of regressions using econometric techniques.

¹³ This suspect is verified in the evaluation of the study educational results of a group of countries carried out by Afonso and St. Aubyn (2005).

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Its main weakness is the impossibility of applying a downwards correction for units classed as efficient in the initial estimation. This appears inappropriate if these units have a relatively high level of non-controllable inputs, which involves a practical requirement when it comes to selecting the technique used in the process related to the characteristics of the available data set¹⁴.

b) *Four stage model (Fried et. al, 1999)*

To distinguish the different effects incorporated in slacks, this model uses a system of equations formed by n Tobit regressions, one for each variable. The dependent variables are the total slacks of each output obtained in the initial DEA and the regressors are the exogenous factors:

$$ITS_j^k = f(Z_j^k, \beta_j, u_j^k)$$

where ITS_j^k represents total slacks obtained in the first stage, Z_j^k is a vector representing non-controllable inputs, β_j is a vector of coefficients and u_j^k is the error term.

From an applied perspective, its output-oriented approach is especially appropriate for including the effect of non-discretionary inputs in the educational sector as this technique only corrects output values -the only variables influenced by these factors-. It can also correct the scores of units considered efficient in the first stage if these have high values of exogenous factors.

The similarity of this method with second stage models means that it shares certain of their limitations. One is of a practical kind, such as the fact that there has to be a significant relationship between the slacks and exogenous variables so that it can be used and another, which is more

¹⁴ This is a decisive factor in the decision of its promoters to abandon it, as described in

important, of a methodological nature to do with problems of bias in the estimation of regressions¹⁵. While the former difficulty affects the possibility of applying it to certain samples, the latter can be overcome by using bootstrap technique when estimating the equations system of the original regressions, though this is an option undeveloped in the literature.

c) *Three stage model with stochastic frontier (Fried, Lovell, Schmidt and Yaisawarng, 2002)*

The model's starting point is that the total slacks obtained in the first stage have three sources: producer inefficiency, the influence of exogenous factors and random noise. To separate these three components, a stochastic frontier is estimated in the second stage with the slacks as dependent variable, the non-controllable inputs as independent variables and a composed error term which differentiates between the effects of inefficiency and statistical noise. The stochastic frontier regression takes the following functional form:

$$s_{ni} = f^n(z_i; \beta^n) + v_{ni} + u_{ni} \quad n = 1, \dots, N \quad i = 1, \dots, I$$

where $s_{ni} = x_{ni} - X_n \lambda \geq 0$ are the total slacks of the outputs (inputs), $f^n(z_i; \beta^n)$ are the deterministic frontiers of feasible slacks, $z_i = [z_{i1}, \dots, z_{ki}]$, are the variables of exogenous factors, β^n are the vectors of the parameters to be estimated and, finally, $v_{ni} + u_{ni}$ represent the errors, with the first component representing random noise $[v_{ni} \approx N(0, \sigma_{vn}^2)]$ and the second ($u_{ni} \geq 0$) representing technical inefficiency. These regressions can be estimated through maximum likelihood, if some assumptions are made.

Fried et. al (2002).

¹⁵ The slacks can also be calculated using the information of the units making up the sample, with the requirement for independence of errors not being fulfilled.

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3 The stochastic nature of the proposed method allows the
4 incorporation in the analysis of the effect of factors not included in it
5 (random noise). This option also corrects the scores of those units
6 considered as efficient in first stage in the case that they have favourable
7 exogenous resources. Finally, it is also useful in identifying possible
8 extreme values or outliers.
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16 With respect to the disadvantages, we may note the excessively
17 favourable criterion it uses to adjust the initial efficiency scores (worse
18 placed unit in all dimensions), which produces final scores remote from the
19 real production possibilities, as well as problems of bias in the estimations
20 given the shortage of independence amongst the composed errors.
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26 **3.3. Criteria to select the most appropriate model**

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30 As can be seen, an analysis of the different options does not allow
31 us to conclude that any one is better than the others, that is, none of them
32 is free of constraint. Thus, the choice amongst them will depend on the
33 characteristics of the available data set, the fulfillment of some
34 requirements and the specific objectives of the study. However, the
35 analysis allow us to draw some conclusions.
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42 First of all, we think that a multi-stage approach is much more
43 suitable than the single-stage option when including non-controllable
44 inputs in efficiency analysis because of different reasons. The most
45 important limitation of the latter option is that its results depend on the
46 number of variables included.
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53 Within multi-stage models, the most recent developments have
54 shown that results obtained with classic second-stage models are invalid.
55 So when the main objective of the study is to identify the relevance (and
56 the sign) of the effect of non-discretionary inputs on efficiency scores, the
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3 approach proposed by Simar and Wilson (2003) will be the most
4 appropriate¹⁶.
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9 Although second-stage models can be very useful to identify the
10 effect of exogenous variables on efficiency, this approach loses some of
11 the information derived from the initial DEA assessment (the non-radial
12 components of inefficiency) and does not allow us to construct new
13 efficiency scores without an upward bias (or downward with an input
14 orientation). Therefore, we think that adjusted value models are the most
15 appropriate approach to deal with non-discretionary inputs if the aim of the
16 study is to obtain new scores in which their effect is included.
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25 Amongst the three alternative proposals considered we prefer the
26 four-stage model rather than the others, provided that bootstrap
27 techniques are applied in the estimation of Tobit regressions to avoid bias.
28 This selection is based on two facts; i) its ability to adjust upward and
29 downward the initial scores without bias; and ii) the regression is the most
30 appropriate mechanism to separate the effect of non-discretionary inputs
31 from the inefficiency in slacks. However, this method can only be used if
32 there is a significant relationship between the initial scores and exogenous
33 variables. Otherwise, the three stage model would be the most appropriate
34 option since the use of DEA in all the stages does not require the
35 existence of such relationship between variables. Nonetheless it must be
36 considered that this approach can lead to an overestimation in the final
37 scores especially for those units with a relatively high level of non-
38 controllable inputs. Finally, although the three stage stochastic model is
39 very useful for detecting the effect of other factors not included in the
40 analysis (random noise), this proposal is not very appropriate because it
41 sets non-real targets for the units (too easy to achieve) and also requires
42 improvements – not yet developed in the literature- to eliminate estimation
43 biases.
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¹⁶ The choice between the algorithm one and two depends on the sample size.

4. EMPIRICAL APPLICATION

In this section we estimate the level of technical efficiency in a group of Spanish high schools in the Extremadura region. The sample comprises eighty public schools in the region for which we have a great deal of information for the 2001-2002 school year on the non-discretionary inputs (obtained from student surveys), the results achieved by pupils in a standard test and the schools' productive factors.

This information is used to estimate the efficiency scores of the schools without including the information about their non-controllable inputs. Subsequently, once the results have been analysed and taking into account the characteristics of the sample, we select an appropriate model to discount the effect of non-controllable inputs and obtain a new estimation of the schools' efficiency.

4.1. Variables

The results achieved by pupils in the University Entrance Exam are used as an output. All students who wish to go to a Spanish University (public or private institutions) must make this common exam on completing their secondary education. Two variables have been constructed using this information. The average mark of pupils passing the exam (MARKS), as an indicator of a qualitative nature, and the percentage of pupils who pass the exam compared to those enrolling in a university course (ACCEPTED).

As controllable inputs, the two variables most often used in the literature as being representative of the factors managed by the schools are chosen¹⁷. The total number of teachers in the school per 100 pupils

¹⁷ Bessent et. al (1982), Smith and Mayston (1987), McCarty and Yaisawarng (1993) or Muñiz (2002) amongst others.

(TEACHERS) and the total current cost per student excluding school personnel costs during the year (COSTS)¹⁸.

The usual difficulty of an absence of available information on the non-controllable inputs has been overcome in our study through a survey of the pupils of all the schools evaluated. These gave twenty-two variables offering information on a large variety of circumstances which may affect pupils' academic performance. However, all of them are not included in the analysis since some are not statistically related to the representative variables of the output and others provide redundant information. Thus, departing from the current bibliography and statistics criteria, eleven variables associated to the most influential factors on academic achievement are selected. Such factors are the socio-economic and family environment of students, their own abilities or the influence of class mates (peer group effect)¹⁹. The variables, defined as the percentage of pupils who fulfil certain requirements, are listed in Table 1 in the Annex.

In any case, given the number of variables, which is still high, and the fact that none of them represents the factors addressed in the literature and mentioned above particularly accurately, we decided to use Principal Component Analysis (PCA)²⁰. This technique makes it possible to summarise all the information available in a lower number of variables with minimum loss of information. These are the variables which will finally

¹⁸ We should point out that, taking into account the type of variables used, the concept of efficiency to be measured is not strictly technical efficiency as one input (costs other than personnel) is expressed in monetary terms, but they are very close to it. However, this cannot be considered as allocative efficiency as we do not include the price of inputs which are clearly unknown in this field.

¹⁹ In the analysis only variables with a clear influence on two measures of output have been included. Ten non-significant variables in the explanation of any one of the output variables have been discarded. Table 2 and 3 show that only 12 variables account for the percentage of students accepted, while 16 are significantly related to the variable MARKS. The variable "GRANT" (percentage of students with a public grant) has been removed because it is significantly correlated to all variables, as can be seen in Table 4 in the Annex (this table shows the Pearson coefficient amongst the 12 significant variables).

²⁰ Smith and Mayston (1987) were the first to recommend the use of this technique in order to reduce the number of non-discretionary factors in the evaluation of the efficiency of schools.

be incorporated in the assessment of efficiency as representative variables of so-called non-controllable inputs.

PCA allows us to identify three components which cover 78% of the original information (see Annex, Table 5). Next, looking at the rotated component matrix, we can verify which variables are associated with each of the variables. Table 6 in the Annex shows that the first factor is comprised of five variables concerning family incomes, level of education and profession of the fathers (in other words, those determining the student's socio-economic environment). The second is comprised of four variables representing pupils' ability, meaning variables related to their academic record and the opinion that parents have about their academic potential. Finally, the third factor is made up of two variables which offer us information about the characteristics of class mates or peer group effect such as those relating to the pupils' aspirations or their efforts to keep their studies up to date.

In summary, for the empirical application we used two variables for school output (MARKS and ACCEPTED), two offering information about inputs controlled by the schools (TEACHERS and COSTS) and three representing non-discretionary inputs (the three components obtained from the eleven variables described above). Table 1 lists the principal statistichs for these variables.

Table 1: Statistical information about the variables

	MINIMI IM	MAXIMI IM	AVERAGE	STANDARD DEV
MARKS	50.28	72.52	59.59	4.0987
ACCEPTED	12.50	86.42	40.33	14.0819
TEACHERS	7.68	13.21	9.64	1.1490
COSTS	65.63	543.86	161.19	66.8621
COMP 1	0.00	4.60	1.3050	1.0000
COMP 2	0.00	5.06	2.6922	0.9993
COMP 3	0.00	5.27	1.8900	1.0000

4.2. Results obtained with a standard DEA analysis

In this section we assess the schools' efficiency by applying a standard DEA, i.e. using only discretionary inputs. As explained earlier, the approach is to maximise outputs and we consider variable returns to scale both to eliminate possible inefficiencies to do with the size of the schools and because it is the correct option in cases where ratios are used in inputs or in outputs (Hollingsworth and Smith, 2003).

The results in Table 7 in the Annex show eight efficient units (HS 12, 18, 24, 31, 44, 52, 56 and 71), which can in turn be divided into two groups. The first (HS 12, 31, 56 and 71) comprises units which have achieved the best results in the University Entrance Exam, and the second (HS 18, 24, 44 and 52) represents those with lower input values. With regards to the inefficient units, those with the lowest scores are those with the worst results in the University Entrance Exam (HS 10, 37, 53 or 64), or those which, in spite of having greater resources, achieved mediocre results (HS 15, 48 or 62).

This initial assessment would be correct if all the schools had pupils with similar characteristics, which is not true in the light of the information contained in Table 1. Therefore it is necessary to include these variables in the evaluation process.

First of all we must test whether our exogenous variables have any influence on initial efficiency scores or not. For that propose we use the second-stage approach with a truncated regression:

$$Scores = \beta_0 + \beta_1 COMP1 + \beta_2 COMP2 + \beta_3 COMP3 + u_i$$

As can be seen in Table 2, the results of the Tobit estimation show that all variables are significantly related to scores. However, those results are invalid, as explained above. In order to avoid the bias, we have

applied the single bootstrapping method proposed by Simar and Wilson (2003)²¹, through which we have confirmed that result, that is, all the variables are significant.

The next step is to obtain new efficiency scores which include the effect of non-discretionary inputs. In principle, we could opt to use this approach, but the scores obtained would not allow us to identify any efficient unit (See Table 7 in Annex) and, consequently, we would not be able to set production and consumption targets for each unit.

Table 2: Results of the Tobit regressions with scores

	<i>McC&Y (1993)</i>	<i>SW (2003)</i>
	<i>Tobit Regression</i>	<i>Tobit with bootstrap</i>
Dependent Variable	DEA Scores	DEA Scores
Constant	1.2985** (0,0238)	1,3162** (0,0247)
CP1	-0.0378** (0,0064)	-0,0473** (0,0079)
CP2	-0.0235** (0,0064)	-0,0263** (0,0071)
CP3	-0.0187** (0,0064)	-0,0205** (0,0069)

Note: The standard errors of the estimated parameters are shown in brackets.

The subscores ** indicate that the parameter estimated is significant at 5 per cent level.

Therefore, since our aim is to obtain scores which discriminate between efficient and inefficient units, we should use an adjusted value model. Furthermore, these models use the total slacks (radial and non-radial components) obtained in the first stage, and all available information from initial DEA is considered.

Amongst different alternatives following this approach we prefer the four stage model (using bootstrap to estimate regressions) rather than other ones, our selection being based on the reasons in Section 3.3. Nevertheless, to apply this model there must be a significant relationship

²¹ We have used the single bootstrapping (Algorithm 1) proposed by those authors because it performs better than Algorithm 2 when the sample is small (80 units).

between non-discretionary inputs and the slacks obtained in the first stage. The results in Table 2 confirm this relationship for all variables (p -values for the three components are very close to 0) both in the estimation of the initial Tobit regressions and the estimation performed using a 10,000 iteration bootstrap process. Therefore, an extended four-stage model has been used to estimate the efficiency of schools with the parameters obtained by the bootstrapping method to adjust the values of outputs in order to include the effect of non-controllable inputs.

Table 3: Results of the Tobit regressions with slacks

Dependent Variable	Independent Variable			
	Slacks Accepted	Slacks Marks	Slacks Accepted with Bootstrap	Slacks Marks with Bootstrap
Constant	30.9050** (2.6931)	21.6691** (1.7208)	30.9112** (2.6790)	21.6763** (1.7084)
CP1	-3.1547** (0.7406)	-2.7603** (0.4732)	-3.1539** (0.7402)	-2.7671** (0.4748)
CP2	-3.8893** (0.7416)	-1.7736** (0.4739)	-3.8794** (0.7401)	-1.7690** (0.4712)
CP3	-2.1842** (0.7411)	-1.3464** (0.4735)	-2.1956** (0.7375)	-1.3497** (0.4733)

Note: The standard errors of the estimated parameters are shown in brackets. The subscores ** indicate that the parameter estimated is significant at 5 per cent level.

4.3. Results from incorporating the effect of non-discretionary inputs

Comparing the scores obtained from the four stage model with the initial scores (Table 4) allows us to draw some conclusions. Firstly, there is an increase in average efficiency. More units benefit from the inclusion of non-discretionary inputs than those which are negatively affected and the efficiency gains outstrip the losses (see Annex, Table 7).

Secondly, the number of efficient units increases to twelve, as a consequence of five becoming efficient (HS 22, 25, 34, 42 and 78), and one (HS 24) no longer being efficient. The new efficient centres have been benefited in the second estimation because the scores assigned to each

unit are constructed taking into account additional resources, thus implying that all the units are evaluated according to their true productive potential.

As with the units which become efficient, there are others, which though they do not reach the frontier, clearly move closer to it. This is the case with the schools like HS 28, 33 ó 36. All were negatively affected in the first evaluation which ignored the type of pupils in each school. However, by applying the four stage methodology, all reduce their score and are amongst the ten best inefficient units.

Table 4: Differences between the initial DEA and the extended four-stage model

	Efficient units	Average efficiency	Percentage of units with a difference > 5%	Spearman's coefficient
Initial DEA	8	1,1504	57.5	0.714
Modified 4 stage	12	1,108		

In the case of the unit that goes from being efficient to inefficient the opposite applies. The first DEA, in which not all the resources are taken into account, benefits this school as it is one of those which have better quality students. However, it can be seen in the subsequent evaluation that the school was not in fact maximising its results given its set of non-controllable factors (Table 8 in the Annex).

Many others also obtain a score which is appreciably higher following the correction made using the four stage model, causing significant changes in the final classification of schools. The most noticeable are those affecting units 20, 50 and 59 which are noteworthy for having a set of non-discretionary inputs which are clearly higher than the others.

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Finally, although the corrections to values are not too significant, a considerable number of units modify their scores. More than half change their score by more than 5% (Table 3). This changes the final ranking of the units as can be seen by the value of the Spearman coefficient range (0.714).

5. CONCLUSIONS

This study offers a detailed analysis of the advantages and disadvantages of different options proposed in the literature for incorporating the effect of non-controllable inputs when estimating efficiency scores. Their inclusion is essential in areas like education where output depends to a large extent on factors, such as socio-economic characteristics of the students and their families, which are outside of the schools' control.

Once certain options which are unsuitable from a methodological perspective have been discarded, it is impossible to say that one model is better than the rest in overall terms. Therefore, the choice will be affected by the specific objectives of the study and the characteristics of the available sample.

These conclusions were followed in estimating the efficiency of a group of Spanish high schools, applying a four stage model proposed by Fried et. al (1999) and adding a bootstrap to avoid problems of bias in the estimations. This approach, which had not been used in the field of education until now, can be considered as a very suitable option to identify the efficient units once the non-discretionary inputs have been included in the analysis.

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ANNEX

Table 1: Definition of the representative variables of non-discretionary inputs

Name of variable	Definition
PASSALL	Pupils who passed all their subjects last year
NOREPEAT	Pupils who have never repeated a year
RECORD	Pupils who passed all subjects between June and September last year with high marks
HOURS	Pupils who studied for more than 10 hours a week
ASPIRATION	Pupils wishing to study at university
PARENTSCONFIDENCE	Pupils whose parents have confidence in their academic success
INCOMES	Pupils whose parents have high incomes
FATHEREDUC	Pupils whose father has a university education
MOTHEREDUC	Pupils whose mother has a university education
FATHERJOB	Pupils whose father is a qualified professional
MOTHERJOB	Pupils whose mother is a qualified professional

Table 2. Individual regressions with "ACCEPTED" as dependent variable

	COEFFICIENT	T-STATISTIC	PROB.
SEX	0,1531	1,3599	0,1775
PASSALL	0,2178	2,8795	0,0051
RECORD	0,1729	2,0462	0,0461
NOREPEAT	0,2574	3,6004	0,0005
PRERECORD	0,1751	1,7866	0,0777
HOURS	0,2315	2,8532	0,0055
STUDY	0,0617	0,2822	0,7785
ASISSTENCE	0,1055	1,2469	0,2159
ASPIRATION	0,3747	5,1959	0,0000
SELFCONFIDENCE	0,1649	1,3592	0,1778
PARENTSCONFIDENCE	0,2262	2,2080	0,0300
TEACHERSCONFIDENCE	-0,2024	-1,2283	0,2228
PARandTEACHCONFIDENCE	0,1878	1,7437	0,0849
INCOMES	0,1828	2,0214	0,0465
FATHEREDUC	0,2107	2,0577	0,0428
MOTHEREDUC	0,2860	2,6666	0,0092
FATHERJOB	0,1634	2,6125	0,0107
MOTHERJOB	0,2964	3,2808	0,0015
GRANT	0,2932	3,6927	0,0004
ONLYCHILD	0,1432	0,5494	0,5842
CHANGESCHOOL	0,0595	0,5125	0,6097
UNIVERSITY	0,1531	1,3599	0,1775

Table 3. Individual regressions with "MARKS" as dependent variable

	COEFICIENTE	ESTADÍSTICO T	PROB.
SEX	0,0214	0,4905	0,6251
PASSALL	0,1078	3,1346	0,0024
RECORD	0,1178	2,7311	0,0077
NOREPEAT	0,1203	3,6811	0,0004
PRERECORD	0,1378	3,1865	0,0020
HOURS	0,0867	2,2919	0,0244
STUDY	0,1963	2,0044	0,0483
ASISSTENCE	-0,0246	-0,6298	0,5306
ASPIRATION	0,1250	3,5204	0,0007
SELFCONFIDENCE	0,1675	3,1484	0,0023
PARENTSCONFIDENCE	0,1347	2,9265	0,0044
TEACHERSCONFIDENCE	0,0839	1,1076	0,2713
PARandTEACHCONFIDENCE	0,1433	2,9991	0,0036
INCOMES	0,1706	4,4742	0,0000
FATHEREDUC	0,1901	4,3815	0,0000
MOTHEREDUC	0,1772	3,7358	0,0003
FATHERJOB	0,1004	3,6197	0,0005
MOTHERJOB	0,1486	3,6321	0,0005
GRANT	0,1476	4,1243	0,0001
ONLYCHILD	0,0851	0,7130	0,4778
CHANGESCHOOL	-0,0568	-1,0730	0,2864
UNIVERSITY	0,0775	1,5042	0,1363

Table 4. Pearson correlation coefficient amongst significant variables

	PALL	REC	NOREP	PACNF	ASPIR	INC	FAEDU	MOEDU	FAJOB	MOJOB	GRANT
PASSALL	1,000										
RECORD	0,679*	1,000									
NOREPEAT	0,602*	0,595*	1,000								
PARCONFID	0,172	0,232	0,266	1,000							
ASPIRAT	0,527*	0,367*	0,463*	0,303*	1,000						
INCOMES	0,250	0,196	0,205	0,104	0,277*	1,000					
FATEDUC	0,288	0,266	0,253	0,226	0,330*	0,830*	1,000				
MOTEDUC	0,335*	0,318*	0,203	0,169	0,317*	0,790*	0,882*	1,000			
FATJOB	0,198	0,088	0,150	0,120	0,314*	0,790*	0,814*	0,766*	1,000		
MOTJOB	0,219	0,152	0,157	0,205	0,265	0,775*	0,776*	0,843*	0,788*	1,000	
GRANT	0,511*	0,398*	0,467*	0,381*	0,624*	0,412*	0,441*	0,416*	0,429*	0,414*	1,000

*Significant correlation at 0,01.

Table 5: Principal Components Analysis for non-discretionary inputs

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	5.145	46.777	46.777	5.145	46.777	46.777
2	2.364	21.489	68.265	2.364	21.489	68.265
3	1.092	9.927	78.192	1.092	9.927	78.192
4	.665	6.048	84.241			
5	.459	4.169	88.409			
6	.371	3.373	91.782			
7	.271	2.465	94.247			
8	.208	1.887	96.135			
9	.193	1.757	97.892			
10	.152	1.381	99.273			
11	.079	.727	100.000			

Table 6: Rotated Factor Matrix (PCA)

	COMPONENT		
	1	2	3
PASSALL	0.107	0.780	0.374
NOREPEAT	0.072	0.690	0.482
RECORD	0.085	0.883	0.126
HOURS	0.057	0.088	0.909
ASPIRATION	0.255	0.416	0.505
CONFIDENCE	0.274	0.773	-0.194
INCOMES	0.888	0.112	0.166
FATHEREDUC	0.915	0.205	0.037
MOTHEREDUC	0.916	0.250	-0.042
FATHERJOB	0.899	0.020	0.190
MOTHERJOB	0.901	0.114	0.049

Rotation Method: Varimax with Kaiser Normalization.

Table 7: Efficiency scores and rankings

	Standard DEA	Rank	SW Model	Rank	4-Stages Model with bootstrap	Rank
HS 1	1,166	46	1,1693	36	1,078	25
HS 2	1,236	71	1,2029	67	1,126	47
HS 3	1,128	26	1,1471	25	1,117	44
HS 4	1,241	72	1,2097	71	1,174	70
HS 5	1,158	39	1,1729	42	1,104	38
HS 6	1,098	19	1,1239	17	1,110	41
HS 7	1,149	33	1,1696	38	1,171	69
HS 8	1,065	11	1,0916	6	1,063	20
HS 9	1,142	30	1,1548	26	1,084	27
HS 10	1,300	79	1,2201	79	1,215	77
HS 11	1,076	14	1,0974	10	1,138	54
HS 12	1,000	4	1,0950	7	1,000	2
HS 13	1,221	67	1,2018	65	1,156	61
HS 14	1,204	59	1,1913	56	1,159	64
HS 15	1,246	74	1,2076	69	1,160	65
HS 16	1,150	34	1,1798	47	1,127	48
HS 17	1,077	15	1,1263	18	1,038	14
HS 18	1,000	5	1,0972	8	1,000	8
HS 19	1,201	56	1,1998	63	1,099	37
HS 20	1,151	35	1,1608	29	1,215	76
HS 21	1,173	51	1,1732	43	1,077	24
HS 22	1,110	22	1,1321	22	1,000	5
HS 23	1,206	63	1,1952	59	1,156	60
HS 24	1,000	2	1,0443	2	1,070	21
HS 25	1,065	10	1,0973	9	1,000	10
HS 26	1,164	45	1,1865	52	1,105	39
HS 27	1,154	37	1,1870	53	1,099	36
HS 28	1,173	49	1,1759	45	1,037	13
HS 29	1,169	47	1,1722	41	1,136	53
HS 30	1,190	54	1,1847	51	1,113	42
HS 31	1,000	8	1,0805	5	1,000	11
HS 32	1,144	31	1,1780	46	1,092	29
HS 33	1,160	40	1,1695	37	1,039	15
HS 34	1,099	20	1,1271	19	1,000	9
HS 35	1,161	41	1,1705	39	1,098	35
HS 36	1,206	64	1,1913	57	1,046	16
HS 37	1,307	80	1,2173	77	1,248	79
HS 38	1,146	32	1,1683	35	1,094	33
HS 39	1,182	52	1,2139	74	1,125	46
HS 40	1,162	43	1,1672	32	1,134	51
HS 41	1,196	55	1,1812	49	1,115	43
HS 42	1,085	17	1,1625	30	1,000	4
HS 43	1,108	21	1,1312	21	1,055	18
HS 44	1,000	1	1,1151	14	1,000	1

HS 45	1,087	18	1,1181	15	1,052	17
HS 46	1,206	61	1,2145	75	1,167	68
HS 47	1,113	23	1,1308	20	1,107	40
HS 48	1,255	77	1,2172	76	1,182	71
HS 49	1,226	68	1,1995	61	1,259	80
HS 50	1,162	42	1,1709	40	1,203	74
HS 51	1,173	50	1,1814	50	1,151	59
HS 52	1,000	6	1,0533	3	1,000	7
HS 53	1,254	76	1,2109	73	1,161	67
HS 54	1,120	24	1,1422	23	1,079	26
HS 55	1,135	28	1,1587	28	1,094	31
HS 56	1,000	7	1,0402	1	1,000	6
HS 57	1,154	38	1,1631	31	1,096	34
HS 58	1,133	27	1,2097	72	1,088	28
HS 59	1,075	13	1,1033	11	1,159	63
HS 60	1,202	58	1,1990	60	1,076	23
HS 61	1,183	53	1,1803	48	1,216	78
HS 62	1,243	73	1,2051	68	1,132	50
HS 63	1,170	48	1,1739	44	1,135	52
HS 64	1,259	78	1,2187	78	1,195	73
HS 65	1,202	57	1,1942	58	1,142	56
HS 66	1,248	75	1,2089	70	1,208	75
HS 67	1,152	36	1,1682	34	1,124	45
HS 68	1,231	70	1,2023	66	1,131	49
HS 69	1,195	55	1,1901	54	1,147	58
HS 70	1,221	66	1,1997	62	1,158	62
HS 71	1,000	3	1,1087	12	1,000	3
HS 72	1,204	60	1,1902	55	1,137	55
HS 73	1,229	69	1,2015	64	1,145	57
HS 74	1,079	16	1,1093	13	1,075	22
HS 75	1,126	25	1,1469	24	1,058	19
HS 76	1,217	65	1,2330	80	1,193	72
HS 77	1,163	44	1,1676	33	1,093	30
HS 78	1,043	9	1,0727	4	1,000	12
HS 79	1,068	12	1,1190	16	1,160	66
HS 80	1,141	29	1,1576	27	1,094	32
Average	1,150	-	1,1625	-	1,108	-

Table 8: Non-discretionary inputs for each high school

	PC1	PC2	PC3		PC1	PC2	PC3
HS 1	1.0808	1.4951	1.0187	HS 41	0.2187	2.7987	2.3335
HS 2	1.4212	0.6059	0.1967	HS 42	0.6686	2.1311	2.1477
HS 3	1.8614	3.1401	2.1468	HS 43	0.3599	3.7343	2.2877
HS 4	0.7276	2.7477	2.0753	HS 44	1.9076	1.8234	2.4579
HS 5	1.4026	3.1588	1.3687	HS 45	1.1824	4.3392	1.3264
HS 6	1.9669	2.4983	3.4984	HS 46	0.3398	3.6254	2.7528
HS 7	2.2588	2.6491	3.1852	HS 47	1.0450	3.9637	1.8646
HS 8	0.8083	2.3982	5.2743	HS 48	0.3185	3.4848	0.6267
HS 9	0.6896	3.2240	3.3473	HS 49	1.0532	4.0855	2.9011
HS 10	0.4224	1.8592	1.4136	HS 50	2.0677	4.3398	1.3995
HS 11	4.6013	1.0401	2.0900	HS 51	1.4411	2.7152	2.2873
HS 12	1.3850	3.9275	2.4113	HS 52	3.1948	3.6682	1.6367
HS 13	0.0000	3.3721	2.1315	HS 53	0.5786	1.7482	1.7943
HS 14	1.5857	2.0269	1.3725	HS 54	1.2085	2.6764	2.2443
HS 15	1.0413	0.6457	2.3220	HS 55	1.3972	2.8984	2.3295
HS 16	0.9165	4.4271	1.5982	HS 56	3.6352	5.0613	1.6067
HS 17	1.3560	3.8398	1.4263	HS 57	0.9291	3.0304	1.1858
HS 18	2.4432	2.3563	1.7231	HS 58	1.5084	2.2075	1.4870
HS 19	0.2991	3.2500	0.2965	HS 59	4.4237	2.5879	2.4581
HS 20	2.5508	2.6287	4.0942	HS 60	1.4312	1.8256	1.9502
HS 21	0.5152	2.7861	1.1598	HS 61	1.9006	3.7419	1.8804
HS 22	0.3016	3.1860	1.6239	HS 62	0.9679	1.1688	0.0288
HS 23	0.5144	2.4602	3.0751	HS 63	0.5758	3.5621	2.3229
HS 24	3.5859	3.3580	2.3960	HS 64	0.9592	2.4005	1.2170
HS 25	0.5770	2.6935	3.0344	HS 65	0.8750	3.1157	1.0487
HS 26	0.8750	2.3512	2.2104	HS 66	1.4877	0.6579	3.1975
HS 27	1.0462	3.4355	1.1760	HS 67	1.8478	2.4793	1.4155
HS 28	0.7177	0.0000	1.2093	HS 68	0.2757	2.8287	0.0000
HS 29	0.4964	3.1566	2.4382	HS 69	2.4651	1.9489	0.1295
HS 30	1.2993	3.0063	0.5576	HS 70	0.0480	2.0493	3.7129
HS 31	2.0975	3.5235	2.1756	HS 71	1.4361	2.8011	2.0229
HS 32	0.0925	3.0095	3.6040	HS 72	0.9623	1.6753	2.2555
HS 33	0.1048	2.8841	0.9020	HS 73	1.0699	2.1929	0.4935
HS 34	0.8876	1.5343	2.9837	HS 74	2.6558	3.1612	2.0677
HS 35	1.5845	2.1841	1.3469	HS 75	0.9686	2.0025	2.8209
HS 36	0.5419	0.7101	0.1403	HS 76	0.8843	4.7554	0.3874
HS 37	0.7452	1.6108	2.3759	HS 77	1.6583	1.4129	1.2149
HS 38	2.0752	3.1690	0.9027	HS 78	0.1629	3.6564	1.9776
HS 39	0.2346	3.4821	2.6125	HS 79	3.7948	2.3542	2.1048
HS 40	0.6136	2.7154	2.5032	HS 80	2.7672	2.1222	0.4030
Average	1.3050	2.6922	1.8900	Average	1.3050	2.6922	1.8900