

## Chapter 2

# An Overview of the Existing Literature and Its Linkages with the Present Book

**Abstract** This chapter provides an overview of the existing literature on the technical efficiency of education sector. The concept of output and input oriented measures of technical efficiency is illustrated. After describing the methodology of estimating technical efficiency using different approaches; the nonparametric data envelopment analysis (DEA, the deterministic frontier approach) and stochastic frontier production function, the chapter summarizes different studies of technical efficiency on education sector around the globe on school and higher education along with the relevant studies for the Indian economy. The connection between the existing literature on the technical efficiency of education sector and the book is highlighted.

### 2.1 Introduction

Although Debreu (1951), Koopmans (1951) tried to design some idea on the measurement of efficiency of a producing unit, the effective measurement of Technical Efficiency was started with the analysis of Farrell (1957). He distinguished between Technical Efficiency (TE) and Allocative Efficiency (AE). According to Farrell, in case of TE, a comparison can be made either between observed output and the maximum potential output obtainable from the given inputs (termed as ‘*output-oriented efficiency*’) or between the observed inputs and the minimum possible inputs required to produce a given level of output (termed as ‘*input-oriented efficiency*’). *Input oriented* technical efficiency measure deals with the maximum amount of input quantities, which can be proportionately reduced without changing quantities produced as output. *Output oriented* technical efficiency deals with the maximum output quantities that can be proportionately increased without altering input quantities. In contrast, the AE is defined as the capability of a producing unit to combine inputs and outputs in optimal proportions, given their respective prices and production technology.<sup>1</sup>

Following Farrell’s (1957) substantive theoretical and empirical literature, two alternative methods are observed to measure TE scores of a producing unit—(i) non

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<sup>1</sup>Refer Battese and Coelli (1988, pp. 134–140), Lovell (1993, p. 40).

parametric Data Envelopment Analysis that involves mathematical programming procedures and (ii) Stochastic Frontier Models<sup>2</sup> containing parametric econometric methods. The production frontier is the locus of all maximum possible levels of output that could be produced, using the existing production technology, at all feasible combinations of quantities of various inputs. However, a producing unit, with its observed use of various inputs, may be located below this production frontier—termed as “Technically Inefficient Producing Unit” and the further away it is placed from this frontier, the larger is its extent of Technical Inefficiency.<sup>3</sup>

## 2.2 A Survey of Methodologies for Estimating Technical Efficiency and the Literature on Efficiency of Education Sector

### 2.2.1 *The Survey of Methodologies for Estimating Technical Efficiency*

A production function is the maximum possible output which can be produced from given quantities of a set of inputs. Similarly, a cost function gives the minimum level of cost at which a particular quantity of output can be produced, given input prices. The word ‘frontier’ may be meaningfully applied in each case because the function sets a limit to the range of possible observations. Thus there exist points below the production frontier but no point lie above it (similarly, all observations must lie on or above cost frontier). The amount by which a producing unit lies below its production frontier (or above its cost frontier) can be regarded as a measure of inefficiency. *In efficiency analysis it is not assumed that the production unit always behaves optimally and hence they can operate inefficiently. Efficiency measurement is a two stage problem—In order to judge the performance of the production units, a benchmark production function has to be constructed which is called as frontier, and is supposed to be perfectly efficient. The method of comparing the observed performance of production unit with the postulated standard of perfect efficiency is the basic problem of measuring efficiency.*

In this context a distinction needs to be drawn between Technical Efficiency (TE) and Allocative Efficiency (AE).

Let  $x$  denote the vector of  $n$  inputs that a producing unit uses to produce a single output  $y$ . Let  $p$  denote the vector of input prices, which are assumed to be positive and fixed. Then efficient transformation of inputs into output is characterized by the production function,  $y = f(x)$ , which shows the maximum output  $y$  obtainable from a given combination of inputs  $x$ .

<sup>2</sup>This model was independently developed by Aigner et al. (1977), Meeusen and Broeck (1977).

<sup>3</sup>For detail theory, refer Lovell (1993, p. 40), Coelli et al. (1998, pp. 134–140).

Let  $(y', x')$  be the observed production plan of the firm. This plan is said to be technically efficient if  $y' = f(x')$  and technically inefficient if  $y' < f(x')$ . Clearly, from the definition of the production function  $y'$  cannot exceed  $f(x')$ . A measure of TE is the ratio of  $y'$  to  $f(x')$ , that must lie between 0 and 1.

The observed production plan  $(y', x')$  is said to be allocatively efficient if the ratio of marginal productivities of any two factors is equal to the corresponding factor price ratio

$$\text{i.e. } f_i(x')/f_j(x') = p_i/p_j \text{ for all } i, j$$

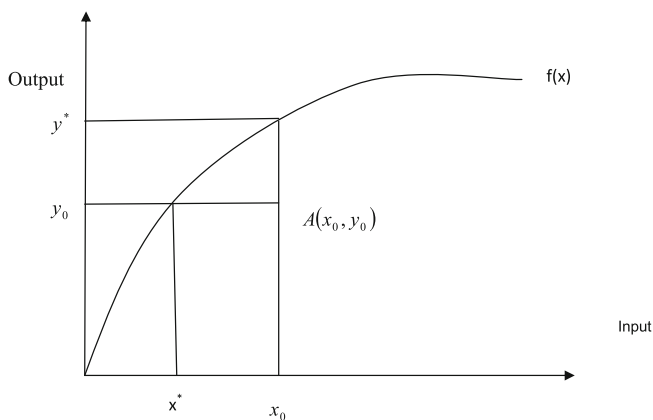
The production plan is allocatively inefficient if this equation is invalid for some pair of inputs.

*The present book deals with the measurement of TE.*

Figure 2.1 shows both the *input and output oriented measures of technical efficiencies* in case of single input and output.

In Fig. 2.1 input  $x$  is measured along the horizontal axis and output  $y$  is measured along the vertical axis. Point  $A(x_0, y_0)$  represents the actual input-output bundle of a DMU,  $A$ . Now  $y^* = f(x_0)$ , where  $y^*$  is the maximum output producible from input  $x_0$ . The *output-oriented* measure of technical efficiency of Decision Making Unit (DMU)  $A = \frac{y_0}{y^*}$  which is the comparison of actual output with the maximum producible quantity from the observed input. Now for the same output bundle  $y_0$ , the input quantity can be reduced proportionately till the frontier is reached. So,  $y_0$  can be produced from input  $x^*$ . Thus the *input-oriented* technical efficiency measure for DMU  $A = \frac{x^*}{x_0}$ . The TE score of a DMU takes a value between 0 and 1. A value of one indicates the DMU is fully technically efficient.

Research on Efficiency Measurement has, since the seminal work of Farrell (1957) bifurcated, with economists typically following the route of Statistical

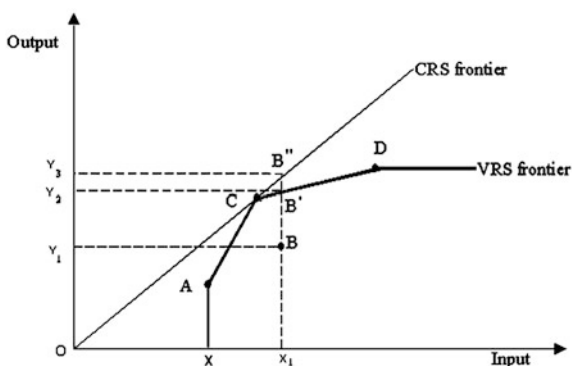


**Fig. 2.1** Output and input oriented measures of technical efficiency

analysis (Aigner et al. 1977) and management scientists characteristically opting for non-parametric route grounded in linear programming (Charnes et al. (CCR) 1978). The former approach has come to be known as Stochastic Frontier analysis, the later as Data Envelopment Analysis (DEA) which is basically a linear programming method. Charnes et al. (CCR) (1978, 1981) introduced the method of DEA to address the problem of efficiency measurement for decision making units (DMU) with multiple inputs and multiple outputs in a school setting. They coined the phrase decision making units to include non-market agencies like schools, hospitals, courts which produce identifiable and measurable output from measurable inputs but generally lack market prices of outputs (and often some inputs as well). Thus, the estimation of efficiency score for primary and upper primary level of education in India with the help of DEA will certainly be an interesting issue. The advantage of DEA analysis basically is that it is not dependent on the prior specification of functional form or the criterion function.

TE of the DMU depends also on the assumption of returns to scale. Two different assumptions can be made, i.e. constant return to scale (CRS) and variable returns to scale (VRS). The CRS describes the fact that output will change by the same proportion as inputs are changed (e.g. a doubling of all inputs will double output). On the other hand, VRS reflects the fact that production technology may exhibit increasing, constant and decreasing returns to scale. If there are economies of scale, then doubling all inputs should lead to more than a doubling of output. Figure 2.2 illustrates the basic ideas behind DEA and return to scale. Four data points (A, C, B', and D) are used here to describe the efficient frontier and the level of capacity utilization under VRS. In a simple one output case only B is inefficient, lies below the frontier, i.e. shows capacity underutilization. So unit B can produce more output at point B' on the frontier (which is equal to theoretical maximum) utilizing same level of input at  $X_1$ . Under CRS the frontier is defined by point C for all points along the frontier, with all other points falling below the frontier (hence indicating capacity underutilization). So capacity output corresponding to VRS is smaller than the capacity output corresponding to CRS.

**Fig. 2.2** The production frontier and returns to scale



The assumption of CRS is restrictive; a more generalized case will be the assumption of VRS. *Using the actual input output bundle* and a number of fairly general assumptions about the nature of the underlying production technology, namely, (i) all actually observed input-output combinations are feasible, (ii) the production possibility set is convex, (iii) inputs are freely disposable, (iv) outputs are freely disposable, with the help of *DEA Banker, Charnes and Cooper (BCC)* (Banker et al. 1984), under VRS *derives a benchmark output quantity without any prior specification of the production frontier* applying a linear programming (LP) problem, with which the actual output of a DMU can be compared for efficiency measurement.

*The present book following BCC estimates both output and input oriented measure of TE using DEA under VRS for primary and upper primary level of education of all the States and union territories in India over the period 2005–06 to 2010–11.*

### 2.2.1.1 Estimation of Output Oriented Measure of Technical Efficiency Using DEA

It is supposed that there are  $N$  firms. Each of them is producing ‘g’ outputs using ‘h’ inputs. The firm  $t$  uses input bundle  $x^t = (x_{1t}, x_{2t}, \dots, x_{ht})$  and produces the output bundle  $y^t = (y_{1t}, y_{2t}, \dots, y_{gt})$ . Technology can either follow CRS or VRS.

The production possibility set corresponding to CRS can be defined as

$$T^{CRS} = \left\{ (x, y) : x \geq \sum_{j=1}^N \lambda_j x^j; y \leq \sum_{j=1}^N \lambda_j y^j; \lambda_j \geq 0; (j = 1, 2, \dots, N) \right\} \quad (2.1)$$

The specific production possibility set under VRS is given by

$$T^{VRS} = \left\{ (x, y) : x \geq \sum_{j=1}^N \lambda_j x^j; y \leq \sum_{j=1}^N \lambda_j y^j; \sum_{j=1}^N \lambda_j = 1; \lambda_j \geq 0; (j = 1, 2, \dots, N) \right\} \quad (2.2)$$

The output oriented measure of TE of any firm  $t$  under *CRS technology* requires the solution of the following LP problem

$$\begin{aligned} & \max \phi \\ \text{Subject to} & \quad \sum_{j=1}^N \lambda_j y_{rj} \geq \phi y_{rt}; \quad (r = 1, 2, \dots, g); \end{aligned}$$

$$\sum_{j=1}^N \lambda_j x_{ij} \leq x_{it}; (i = 1, 2, \dots, h);$$

$$\phi \text{ free, } \lambda_j \geq 0; (j = 1, 2, \dots, N) \quad (2.3)$$

Output oriented TE of firm t can be determined by using Eq. (2.4).

$$TE_o^{ct} = TE_o^{ct}(x^t, y^t) = \frac{1}{\phi^*} \quad (2.4)$$

where  $\phi^*$  is the solution of Eq. (2.3) showing the maximum value of  $\phi$ .  $y^*$  is the maximum output bundle producible from input bundle  $x^t$  and is defined as  $y^* = \phi^* y^t$ . Under VRS,  $\max \phi, \phi^*$ , can be determined by solving Eq. (2.3) along with the constraint  $\sum_{j=1}^N \lambda_j = 1$ , taking into account the VRS frontier (Eq. (2.2)). Knowing  $\phi^*$ , TE of the firm can be solved using similar methodology corresponding to CRS.

### 2.2.1.2 Estimation of Input Oriented Measure of Technical Efficiency Using DEA

The input-oriented measure of technical efficiency of any firm t under CRS requires the solution of the following LP problem

$$\min \theta$$

$$\text{Subject to} \quad \sum_{j=1}^N \lambda_j y_{rj} \geq y_{rt}; \quad (r = 1, 2, \dots, g)$$

$$\sum_{j=1}^N \lambda_j x_{ij} \leq \theta x_{it}; \quad (i = 1, 2, \dots, h)$$

$$\theta \text{ free, } \lambda_j \geq 0, \quad (j = 1, 2, \dots, N) \quad (2.5)$$

The input-oriented technical efficiency of firm t under CRS is

$$TE_{IN}^{ct} = TE_{IN}^{ct}(x^t, y^t) = \theta^* \in T^{CRS} \quad (2.6)$$

where  $\theta^* = \min \theta : (\theta x^t, y^t) \in T^{CRS}$ .

Thus knowing  $\theta^*$  by solving Eq. (2.5) input oriented TE of firm t can be determined by using Eq. (2.6).

The input oriented measure of TE of any firm t under VRS can be determined by solving problem (2.5) along with the constraint  $\sum_{j=1}^N \lambda_j = 1$ , considering VRS frontier.

### 2.2.1.3 Representation of Input Slack

In LP models radial measures of efficiency is obtained. Here efficiencies are measured along a ray from the origin to the observed production point. In such a radial projection of an observed input-output bundle onto the frontier, sometimes all the inputs used are not potentially reduced. The horizontal or vertical portion of an isoquant accounts for inefficiency in usage of inputs. As a result there may be the possibility of the existence of input slack for the case of multiple input output production process. Among the output produced by firm  $t$ , the largest output bundle with the same output mix as  $(y_1^t, y_2^t)$  that can be produced from the input bundle  $(x_1^*, x_2^*)$  is  $(\phi^* y_1^*, \phi^* y_2^*)$ .

It is sometimes possible to expand individual outputs by a factor larger than  $\phi^*$ . It is also possible that firm  $t$  may not entirely use up all the individual components of the input bundle to produce the expanded output bundle. Hence all the inputs used are not potentially reduced.

The input slack variable can be defined as

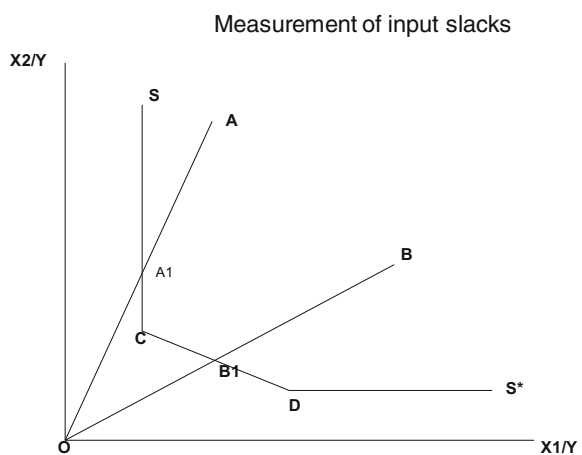
$$s_i^- = x_{it} - x_{it}^*, \quad (i = 1, 2, \dots, h)$$

### 2.2.1.4 Representation of Underutilization of Inputs

The existence of inefficiency in input utilization basically implies existence of radial and or slack movement. The extent of underutilization of input can be measured by sum of radial and slack movement.

The input slack is explained in Fig. 2.3.

**Fig. 2.3** Measurement of input slack



In the Fig. 2.3 c, d are two efficient DMU which are on the frontier. DMU A and B are inefficient. Point  $A_1$  is on the frontier but here also the DMU is inefficient as one can reduce the amount of  $x_2$  input by  $CA_1$  and still produce the same output. So  $CA_1$  is the input slack movement of input  $x_2$  while  $AA_1$  is the input radial movement. The underutilization of input is the sum of this radial and slack movement.

### 2.2.1.5 Estimation of Technical Efficiency Using Deterministic Approach

Let us consider a deterministic production frontier  $f(x_i, t; \beta)$  representing the maximum producible output for the  $i$ th producing unit, under the time index  $t$ , given the non-negative input vector  $X_i$ , with the corresponding technology parameter vector  $\beta$ , representing technology available in the period under consideration. However, the observed output ( $Y_i$ ) of that particular  $i$ th producing unit may lie below the frontier output  $f(x_i, t; \beta)$  in a particular period for various reasons. For instance, the producing unit's workers may not put required effort and/or have lower ability to produce. Some owner and/or supervisor may have lower managerial capability of monitoring the effectiveness of their subordinates (Ray 2004). It can also be argued that in absence of any a priori engineering relation (that associates the combinations of inputs into their respective maximum feasible outputs), in practice, the input-output relation can only turned out to be an estimated one and hence it is quite possible that a given producing unit may not attain its maximum potentiality. This shortfall is actually attributed to the presence of technical inefficiency in that producing unit.

Given this, the production behavior of  $i$ th producing unit can be expressed as

$$Y_i = f(x_i, t; \beta) \exp(-u_i), \dots, u_i \geq 0 \quad (2.8)$$

and a measure, termed as 'output-oriented Farrell measure' of Technical Efficiency ( $TE_i$ ) of  $i$ th producing unit can be given by the ratio of the actual output to the frontier output:

$$TE_i = \frac{Y_i}{f(x_i, t; \beta)} = \exp(-u_i), \dots, u_i \geq 0 \quad (2.9)$$

With  $\exp(-u_i) \cong 1 - u_i$ , the measure of TE ranging between 0 and 1 and varies inversely with  $u_i$ . When  $u_i = 0$ ,  $\exp(-u_i) = 1$  implying no inefficiency, so alternatively,  $u_i$  may be considered as an index of Technical Inefficiency.

The limitation of this deterministic approach is that the frontier outputs for various levels of inputs are not at all affected by any random factors like, weather, strike or by any other unforeseen factors. Aigner et al. (1977), Meeusen and Broeck (1977) independently suggested an alternative model (stochastic model) for production behavior to overcome the limitation.



### 2.2.1.6 Stochastic Approach

In this model an additional random error ‘ $v$ ’ is introduced, apart from the non-negative random variable  $u$ . That particular  $v$  captures the possible unobserved random effects. This model is known as Stochastic Frontier Production Function (SFPF) model in which the frontier itself is subject to all the stochastic variations that are outside the control of the producer.

Here we have considered a stochastic production frontier of the following form:

$$Y_i = f(X_i, t; \beta) \exp(v_i) \quad (2.10)$$

This production frontier represents the maximum possible output producible with the input vector used by the  $i$ th producing unit.

$\beta$  = the corresponding vector of technology parameters

$v_i$  = a random variable seeking to capture all the random factors that are outside the control of the producer (such as, weather, strikes, factor intensity, implementation of some reform policies, natural calamities etc.). These random factors are likely to affect the production of maximum possible output.  $t$  = time period.

Actually, the  $i$ th producing unit’s observed output,  $Y_i$  may lie below the frontier output due to say, the presence of workers with lower ability, poor management decisions or inadequate monitoring efforts etc. These shortfalls are captured by Technical Inefficiency of the producing unit. Since the actual output can not be higher than the frontier output, Eq. (2.10) can be modified as

$$Y_i = f(X_i, t; \beta) \exp(v_i) \exp(-u_i) \quad (2.11)$$

with  $u_i \geq 0$  implying that  $\exp(-u_i) \leq 1$ .

So, an output-oriented Farrell measure of time-varying TE of the  $i$ th producing unit can be presented by

$$TE_i = \frac{Y_i}{f(X_i, t; \beta) \exp(v_i)} = \exp(-u_i) \quad (2.12)$$

for  $u_i \geq 0$  and  $TE_i$  varies inversely with  $u_i$ ,  $0 \leq TE_i \leq 1$ .  $u_i$  may be taken as index of inefficiency. The output-oriented time-varying TE for  $i$ th producing unit is simply the ratio of the actual output to the frontier output.

To estimate the time-varying technical inefficiency prevailing across different firms in a particular industry, the methodology of Battese and Coelli (1993), Lundvall and Battese (2000) can be followed. From Eq. (2.12), it can be noted that  $v_i$  and  $u_i$ —two error terms are included in the expression.  $v_i$  is the usual error term of the model and is independently, identically, normally distributed with mean = 0 and variance =  $\sigma^2$ .  $u_i$  measures the magnitude of technical inefficiency in production prevailing in the  $i$ th producing unit. It is independently distributed from a normal distribution with mean =  $\mu_i$  and variance =  $\sigma_u^2$ , truncated at zero. Further it is assumed that there is no correlation between  $v_i$  and  $u_i$ .

After getting different TE scores of different producing units, one may be naturally interested to stagger on the factors responsible behind the variations in TE scores. To find out the determinants of TEs, some empirical studies have suggested a two-stage procedure. In the first stage, firm-specific TE scores are estimated applying stochastic frontier production functions and in the second stage, the estimated TEs scores are regressed on a number of firm-specific variables like, firm size, capital intensity, trade-related factors etc. It is supposed that these factors might be responsible for the variations in TEs across producing units. In many cases, this two-stage procedure have yielded satisfactory results but it has long been argued that this procedure suffers from an inconsistency problem, originated from the assumption of constant  $\exp(u_i)$  in the first stage, which may contradict the assumption in the second stage that the predicted efficiencies vary with the firm-specific explanatory variables (Coelli et al. 1998, pp. 207–209; Kumbhakar and Lovell 2000, pp. 262–264).

An alternative approach, developed by Battese and Coelli (1993), can be followed in which the estimation of TE scores and the explanation behind the variations in TE are done simultaneously in a single stage. In our empirical study, we have followed this single-stage procedure.

In this model,  $u_i$ s are not assumed to follow an identical distribution, rather different  $u_i$ s should have different means i.e., for each  $u_i$  the corresponding mean, before truncation, can be denoted by  $\mu_i$ ,  $\forall i = 1(1)n$ . So the assumption regarding the variable  $u_i$  is now modified as the following:  $u_i$ s are independently distributed with same variance  $\sigma_u^2$ , but the mean of each  $u_i$  is different to each other:  $u_i \sim idN^+(\mu_i, \sigma_u^2)$ . The present model is now specified with such a stochastic frontier model in which the inefficiency effects are included as an explicit function of some firm-specific factors/variables and their associated parameters. The SFPF along with the inefficiency effects is estimated through a single-stage Maximum Likelihood Estimation (MLE) method.

The mean Technical Inefficiency is represented by

$$\mu_i = \delta'Z_i \quad (2.13)$$

and adding the relation with Eq. (2.11) we get the model for our empirical study. In Eq. (2.13),  $\mu_i$  = mean before truncation for the variable  $u_i$ .

$Z_i$  =  $i$ th producing unit's specific vector that may include exogenous and endogenous variables in explaining the inefficiency effect.

$\delta$  = associated parameters to be estimated and  $\delta'$  is the transpose of  $\delta$ .

It can be noted here that this assumption is consistent with the assumption that the  $u_i$  is a non-negative truncation of  $N(\delta'Z_i, \sigma_u^2)$ . Furthermore,  $u_i$  is specified in such a manner that we can easily obtain the density function of  $u_i$  conditional on  $\varepsilon_i = v_i - u_i$  as well as the expected value of  $TE_i$ , given  $\varepsilon_i$ .<sup>4</sup> There may be some literature in which some alternative models are also presented for this purpose but it can be

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<sup>4</sup>According to Battese and Coelli (1988, 1993), the expected value of  $TE_i$ , given  $\varepsilon_i$  is  $E[\exp(-u_i)|\varepsilon_i]$ .

noticed here that those models are obtained as particular cases of the models following the Eqs. (2.11) and (2.13). For example, according to Huang and Lin (1994), a non-neutral model can be built if some of the input variables of the model also appear in  $Z_i$ . Again, if  $Z_i$  vector's first element is unity with non-zero parameter associated with it, while rest of the  $\delta$  s are zero, we can get the general truncated normal distribution for the  $u_i$  (proposed by Stevenson 1980; Battese et al. 1988). If elements of  $\delta$  is a null vector, the half-normal distribution for the  $u_i$ s are obtained. It is to be noted here that  $Y_i$  should not be included in the  $Z_i$  vector;  $Z_i$  may be defined in terms of the level of an input, but not output

### 2.2.2 Estimation of Technical Efficiency Score for Education Sector

*TE scores is estimated mainly by applying non-parametric Data Envelopment Analysis (DEA) which basically rests on assumed production relationship between input and outputs. In the literature, estimation of efficiency of a school is basically rests on assumed production relationship between input and outputs. Following Ray (2004) educational production function can be defined as:*

$$Y = A (X_1 \dots X_m),$$

where  $Y$  is some measure of school output—for example, enrolment ratio and or marks obtained in standardized examination system.

$X_1, \dots, X_m$  are the variables measuring the school environment. The variables here would typically include the amount and quality of teaching services, the physical infrastructure or facilities of the school.

The term  $A$  can be thought of as a shift parameter, being a function of (i)  $I_1, \dots, I_n$ , the variables representing favourable Infrastructure facilities that promote TE level, (ii)  $PR_1, \dots, PR_q$ , the variables representing the poor infrastructure facilities that can reduce TE level, (i)  $Z_n, \dots, Z_p$  the variables representing environmental influences on learning outside the school—These variables take care of the general environment of learning that the students faces.

Educational achievement can be viewed as a production process, where inputs of resources are applied to the relatively “unfinished” child, and an output-pupil achievement results. The objective is to generate the maximum achievement using a given amount of school resources. Some studies also uses Stochastic Production Frontier Model.

#### 2.2.2.1 International Literature Relating to Studies on Technical Efficiency of Education Sector

A number studies are available dealing with estimation of TE score of the school and higher education, Universities and Research Institutes and also for Further Education around the globe.

### International Literature Relating to Studies on Technical Efficiency of Schools

Mancebon and Eduardo (1999) evaluated the efficiency of a sample of Spanish secondary schools, paying particular attention to the theoretical specification of the measurement model. They tried to demonstrate that, in order for a study of this nature to have the minimum solvency, it is the special characteristics of the education production process that must form the basic guidelines to be followed by researchers. They also highlighted the characteristics that differentiate the most efficient schools from the least efficient, and emphasized the importance of completing the information supplied by the quantitative methods of educational evaluation (such as data envelopment analysis), with the data of qualitative nature obtained by way of surveys directed at the pupils (customers) and the school decision-makers.

Chakraborty et al. (2001) uses both the stochastic and nonstochastic production function approach to measure technical efficiency in public education in Utah. The stochastic specification estimates technical efficiency assuming half normal and exponential distributions. The nonstochastic specification uses two stage data envelopment analysis (DEA) to separate the effects of fixed inputs on the measure of technical efficiency. The empirical analysis shows substantial variation in efficiency among school districts. Although these measures are incentive to the specific distributional assumptions about the one-sided component of the error term in the stochastic specification, they are sensitive to the treatment of fixed socio-economic inputs in the two-stage DEA.

Lassibille and Tan (2001) examined whether explosive growth of private secondary schools in Tanzania led to efficient operations in terms of student learning by comparing the efficiency of four types of schools that make up the majority of schools in the country: Government and Community schools in the public sector, and Christian and Wazazi schools in the private sector. Using longitudinal data from a 1994 retrospective survey of students in some 150 schools, they estimated separate achievement models for these four school types, with corrections for possible selection bias in school choice, and then used the results to simulate performance gaps across them. The simulations indicate that both types of private schools are less efficient than both types of public schools in the sense that, on average, a student with a given set of personal and family characteristics would do better in either type of public school than in either type of private school, after netting out differences in the endowment of school resources across school types. In the public sector, they found that Community schools are more efficient than Government schools. Based on their study they suggested the need for a strong and productive private sector, and recommend the creation of networking opportunities for private school managers to exchange experiences with their public-school counterparts, and the creation of mechanisms for private schools to compete for public funding to support their operations.

Mizala et al. (2002) assesses the technical efficiency of schools in Chile, which is defined as the capacity of schools to generate the maximum output (academic

achievement) given the quantity of inputs they use. Two alternative methodological approaches for measuring efficiency are used stochastic production frontier and DEA. Each of these techniques has advantages and limitations, which are discussed in the paper; they lead, however, to the same conclusions when a sample of 2000 schools is analyzed. The results obtained provide interesting points for educational policy discussion in Chile.

Barbetta and Turati (2003) dealt with the role of proprietary structure in explaining efficiency within the Italian school industry taking a sample of 497 schools located in Piemonte, a region in the North-Western part of the country and distinguishing between public, private for-profit and private nonprofit schools. In stage one of the analyses, they provide robust estimates of efficiency scores, using the two most widely known techniques in applied works, namely DEA and Stochastic Frontiers. In stage two, they suggested that proprietary structure matters in explaining efficiency. Nonprofit schools are more efficient than public ones, whereas for-profit counterparts are outperformed by public producers. Moreover, it was that foreign and disabled students affect negatively efficiency, raising concerns for cream-skimming practices among private producers. Finally, school size is another important determinant of efficiency.

Oliveira and Santos (2005) used Free Disposal Hull (FDH) reference technology that contains information both on inputs and outputs to determine radial technical efficiency scores and slacks for a sample of Portuguese secondary schools. This is the study using FDH at the school level, effectively relaxing the convexity assumption. A two-stage approach is used, whereby the significant environmental variables that explain FDH efficiency scores and slacks are identified. For the purpose of statistical inference, the first application of the bootstrapping algorithms suggested by Simar and Wilson (2004) is conducted. The study concludes that the unemployment rate, access to health care services, adult education and living infrastructures are determinants of school efficiency. The differences between the coast and the interior of Portugal seem to be more relevant, as far as school efficiency is concerned, than whether or not the school belongs to one of the major coast metropolitan areas.

Borge and Naper (2005) performs an efficiency analysis of the lower secondary school sector in Norway. The efficiency potential is calculated to 14 % based on a DEA analysis with grades in core subjects (adjusted for student characteristics and family background) as outputs. The analysis of the determinants of efficiency indicates that a high level of municipal revenue, a high degree of party fragmentation, and a high share of socialists in the local council are associated with low educational efficiency. The negative effects of the share of socialists and party fragmentation seem to reflect both higher resource use and lower student performance.

Grosskopf et al. (2014) compares TE of charter school primary and secondary campuses with that of comparable campuses in traditional Texas school districts. Charter schools are hybrids—publicly funded, but not required to meet all the state regulations relevant for traditional schools. Student performance is measured using value added on standardized tests in reading and mathematics, and efficiency is measured using the input distance function. The analysis suggests that at least in Texas, charter schools are substantially more efficient than traditional public schools.

Naper (2010) analyzed the relationship between teacher hiring practices and educational efficiency in Norwegian school districts. The hiring decision is made at the school level by the principal or at the school district level. According to the data, efficiency is the highest in districts where hiring is decentralized. Hiring practices are decided by the school district, and linear estimates of the effect of decentralized hiring on efficiency may be biased because of non-random selection. First, he approaches this problem by including a large set of controls in a school district level analysis, which does not alter the qualitative result. Second, he performs a school level analysis with district fixed effects. The results indicate, as expected, that the effect of decentralization is stronger for schools facing excess teacher supply than for schools without excess supply.

Alexander et al. (2010) conducted a two-stage (DEA and regression) analysis of the efficiency of New Zealand secondary schools. Unlike previous applications of two-stage semi parametric modeling of the school “production process”, they use Simar and Wilson’s double bootstrap procedure, which permits valid inference in the presence of unknown serial correlation in the efficiency scores. They are therefore able to draw robust conclusions about a system that has undergone extensive reforms with respect to ideas high on the educational agenda such as decentralized school management and parental choice. Most importantly, they find that school type affects school efficiency and so too does teacher quality.

Burney et al. (2010) examined the efficiency of public schools in Kuwait over each school level (kindergarten, primary, intermediate, and secondary) and six academic years (1979/80, 1984/85, 1989/90, 1994/95, 1999/2000 and 2004/05). The analysis is based on the entire public school population in the country and relies on a two-stage approach. In the first stage, estimates of technical, scale, allocative, and economic efficiencies are obtained on the basis of DEA technique. The second stage relates to finding out determinants of TE using school characteristics employing the Tobit regression model. The explanatory variables included in the regression model are the schools’ regional location, teachers’ salary, proportion of teaching staff that are Kuwaitis, and whether a school is all-boys’ or all-girls’. The estimates show that the public schools in Kuwait use more resources for the level of school output, operate below the optimum size (returns to scale are generally increasing), and use non-optimal input proportions. Teachers’ salary is found to have positive effect on technical efficiency while the proportion of Kuwaiti teaching staff has a negative impact. All-girls schools are found to have higher efficiency than all-boys schools.

Cherchye et al. (2010) presented a nonparametric approach for efficiency and equity evaluation in education using a nonparametric DEA. The model accounts for the fact that typically minimal prior structure is available for the behavior (objectives and feasibility set) under evaluation. It allows for uncertainty in the data, while it corrects for exogenous ‘environmental’ characteristics that are specific to each pupil. They propose two multidimensional stochastic dominance criteria as naturally complementary aggregation criteria for comparing the performance of different school types (private and public schools). While the first criterion only accounts for efficiency, the second criterion also take equity into consideration. The model is applied for comparing private (but publicly funded) and public primary

schools in Flanders. The application finds that no school type robustly dominates another type when controlling for the school environment and taking equity into account. More generally, it demonstrates the usefulness of the nonparametric approach, which includes environmental and equity considerations, for obtaining 'fair' performance comparisons in the public sector context.

Kirjavainen (2012) used different stochastic frontier models for panel data to estimate education production functions and the efficiency of Finnish general upper secondary schools. Grades in the matriculation examination are used as an output and explained with the comprehensive school grade point average, parental socioeconomic background, school resources, the length of studies and the decentralization of test-taking. Heterogeneity across schools is allowed for by estimating true random effect (TRE), random parameter (RP) and true fixed effect (TFE) models. The results show that inefficiency and rankings of schools based on their inefficiency scores vary considerably depending on the type of stochastic frontier model applied. The lowest estimates for inefficiency are obtained with TRE, RP and TFE models, which separate time-constant random or fixed effects from inefficiency. The length of studies and the decentralization of test-taking negatively affect student achievement.

Aristovnik (2013) measured relative efficiency in utilizing public education expenditures in the new EU member states in comparison to the selected EU (plus Croatia) and OECD countries. As resources allocated to education are significantly limited, a special emphasis should be given to their efficient use regarding the institutional and legal constraints. An analysis of (output-oriented) efficiency measures by using DEA shows that among the new EU member states Hungary, Estonia and Slovenia seem to be good benchmark countries in the field of primary, secondary and tertiary education, respectively. The empirical results also suggest that, in general, new EU member states show relatively high efficiency in tertiary education efficiency measures.

Agasisti (2013) using DEA computed efficiency scores for a sample of Italian schools by employing OECD-PISA2006 data aggregated at school level. Different versions of the DEA models were estimated to test result robustness, including a DEA bootstrapping procedure. In a second-stage analysis, the factors affecting school efficiency are investigated through a Tobit regression. Among these factors, alternative indicators of competition were included. The results show that at least one indicator of competition is statistically associated with higher performances of schools, suggesting that there is a potential role for improving school results by increasing the number of schools competing each other.

Cuellar and Felipe (2014) appraised quantitatively the efficiency of public expenditure of 15 Latin American countries using cross-country data for averages between 2000 and 2009. For this purpose two non-parametric methods are used: DEA and Free Disposal Hull (FDH). Selected output indicators in primary and secondary school are evaluated respect to public spending in education per student. As a study case, Colombia's efficiency scores are compared with the most efficient peers in each of the educational levels to identify best practices and achieve better results.

Blackburn et al. (2014) applied a public sector DEA model to estimate the efficiency of Australian primary and secondary schools. Standard microeconomic



production theory showing the transformation of inputs into outputs is extended to allow nondiscretionary environmental variables characteristic of educational production. Failure to properly control for the socioeconomic environment leads to inappropriate comparisons and biased efficiency estimates. They employ a conditional estimator that does not allow a school with a better environment to serve as a benchmark for a school with a worse environment. The results suggest that Australian schools are moderately inefficient and that efficiency increases for the quintile of schools with the most favorable environment. Further, efficiency gains are realized with increasing enrollment.

Bogetoft et al. (2015) focusing in particular on upper secondary education examined whether the relatively high level of expenditure on education in the Nordic countries is matched by high output from the educational sector, both in terms of student enrolment and indicators of output quality in the form of graduation/completion rates and expected earnings after completed education. The paper uses DEA to compare (benchmark) the Nordic countries with a relevant group of rich OECD countries and calculate input efficiency scores for each country. The paper estimates a wide range of specifications in order to analyze different aspects of efficiency. In purely quantitative models (where inputs and outputs are expenditure and number of students at different levels of the educational system) and in models where graduation or completion rates are included as indicators of output quality, Finland is the most efficient Nordic country (often fully efficient), whereas Sweden and especially Norway and Denmark are clearly inefficient. However, using PISA test scores as indicators of student input quality in upper secondary education reduces the inefficiencies of these three countries. Also, when expected earnings after completed education are used as an indicator of output quality, all Nordic countries are estimated to be fully efficient (or nearly so).

### International Literature Relating to Studies on Technical Efficiency of Higher and Further Education

Ng and Li (2000) utilizing data from 84 key Chinese higher education institutions attempted to examine the effectiveness of the Education Reform implemented in the mid-1980s in China. With focus on the research performance of the institutions, individual institution efficiency is computed by the method of data envelopment analysis. Regional differences in the efficiency of the institutions are also addressed. It is found that research performance of institutions across regions has improved, although the institutions as a whole have remained inefficient 1993–1995. Institutions located in the East region turn out to have out-performed those in the Central and the West regions. In addition, the decomposition of the group efficiency measure indicates that, for the 3 years under study, the 84 key institutions suffered from technical, allocative and reallocation inefficiency.

Abbott and Doucouliagos (2002) used Data Envelopment Analysis to derive estimates of the technical and scale efficiency of Victorian Technical and Further Education Institutes in 1995. The results reveal substantial dispersion in technical



and scale efficiencies. Regression analysis is used to identify variables which are associated with technical inefficiency.

Flegg et al. (2004) applied DEA to examine the technical efficiency (TE) of 45 British universities in the period 1980/81–1992/93. This period was chosen primarily because it was characterized by major changes in public funding and in student: staff ratios. To shed light on the causes of variations in efficiency, TE is decomposed into pure technical efficiency, congestion efficiency and scale efficiency. The analysis indicates that there was a substantial rise in the weighted geometric mean TE score during the study period, although this rise was most noticeable between 1987/88 and 1990/91. The rising TE scores are attributed largely to the gains in pure technical efficiency and congestion efficiency, with scale efficiency playing a minor role. The Malmquist approach is then used to distinguish between changes in TE and inter temporal shifts in the efficiency frontier. The results reveal that total factor productivity rose by 51.5 % between 1980/81 and 1992/93, and that most of this increase was due to a substantial outward shift in the efficiency frontier during this period.

Ferrari and Laureti (2005) modeled the human capital formation in the Italian university and utilizes a measure of TE to estimate the output-efficiency of human capital formation in the University of Florence, by using DEA on a selected set of inputs and outputs. It uses the Program Evaluation procedure as well, in an attempt to attribute shares of the variation in efficiency to factors that are beyond the control and factors that are under the control of the graduates and faculties.

Johnes (2006a) applied DEA and multilevel modeling to a data set of 54,564 graduates from UK universities in 1993 to assess whether the choice of technique affects the measurement of universities' performance. A methodology developed by Thanassoulis and Portela (2002; *Education Economics*, 10(2), pp. 183–207) allows each individual's DEA efficiency score to be decomposed into two components: one attributable to the university at which the student studied and the other attributable to the individual student. From the former component, a measure of each institution's teaching efficiency is derived and compared to the university effects from various multilevel models. The comparisons are made within four broad subjects: pure science, applied science, social science and arts. The results show that the rankings of universities derived from the DEA efficiencies which measure the universities' own performance (i.e., having excluded the efforts of the individuals) are not strongly correlated with the university rankings derived from the university effects of the multilevel models. The data were also used to perform a university-level DEA. The university efficiency scores derived from these DEAs are largely unrelated to the scores.

McMillan and Chan (2006) determined efficiency scores for Canadian universities using both DEA and stochastic frontier methods for selected specifications. The outcomes are compared. There is considerable divergence in the efficiency scores and their rankings among methods and specifications. An analysis of rankings, however, reveals that the relative positions of individual universities across sets of several efficiency rankings (e.g., all the data envelopment analysis and stochastic frontier outcomes) demonstrate an underlying consistency.

High-efficiency and low-efficiency groups are evidenced but the rank for most universities is not significantly different from that of many others. The results emphasize the need for caution when employing efficiency scores for management and policy purposes, and they recommend looking for confirmation across viable alternatives.

Johnes (2006b) examined efficiency in the context of higher education with an application of DEA to a data set of more than 100 Higher Education Institute (HEIs) in England using data for the year 2000/01. Technical and scale efficiency in the English higher education sector appear to be high on average. The Pastor, Ruiz and Sirvent (2002). Test for comparing nested DEA models is useful in reducing the full model to a smaller 'significant' set of inputs and outputs. Thus, the quantity and quality of undergraduates, the quantity of postgraduates, expenditure on administration, and the value of interest payments and depreciation are significant inputs to, and the quantity and quality of undergraduate degrees, the quantity of postgraduate degrees and research are significant outputs in the English higher education production process. The possibility of differences in the production frontier (and hence the distribution of efficiencies) of three distinct groups of HEIs is explored using a test proposed by Charnes et al. (1981. *Management Science*, 27(6), 668–697) but no significant differences are found. Bootstrapping procedures, however, suggest that differences between the most and least efficient English HEIs are significant.

Fernando and Emilyn (2007) estimated relative efficiency and productive performance of 13 colleges at the University of Santo Tomas (UST), using data envelopment analysis (DEA)—Malmquist indices and a multi-stage model. Total factor productivity (TFP) is measured for a sample of 13 colleges at UST over the period 1998–2003. Empirical results show that the main contributing factor to TFP growth is efficiency change. That is, UST colleges are technically operating efficiently in the frontier technology; though there is a downward shift in the technological advancement. The results further imply that with the use of output–input mix, UST colleges as a whole have recorded a higher level of technical efficiency than innovation. These new findings contribute significantly to the existing literature on efficiency and productive performance in the education sector.

Johnes (2008) used a distance function approach to derive Malmquist productivity indexes for 112 English higher education institutions (HEIs) over the period 1996/97 to 2004/5. The analysis shows that HEIs have experienced an annual average increase in productivity of 1 %. Further investigation reveals that HEIs have enjoyed an annual average increase in technology of 6 % combined with a decrease in TE of 5 %. Rapid changes in the higher education sector appear to have had a positive effect on the technology of production but this has been achieved at the cost of lower technical efficiency.

Agasisti and Johnes (2009) employed DEA to compute TE of Italian and English higher education institutions. The results show that, in relation to the country-specific frontier, institutions in both countries are typically very efficient. However, institutions in England are more efficient than those in Italy when we compare jointly their performances. They also look at the evolution of technical efficiency scores over a four-year period, and find that, in line with an

error-correction hypothesis, Italian universities are improving their technical efficiency while English universities are obtaining stable scores. Policy implications are also addressed.

Agasisti and Bianco (2009) analyzed the effects of teaching reforms in Italy by estimating TE of higher education using DEA. These were introduced in 1999, and changed the entire organization of university courses, where the Bachelor-Master (BA-MA) structure was adopted. The changes introduced by the reforms are modeled within the adopted framework: the effects of teaching reforms are investigated as determinants of efficiency improvements. Malmquist index analysis, suggest that efficiency of the higher education sector as a whole improved in the period 1998/1999 to 2003/2004. Despite the fact that teaching reforms led to worse performance in the first year, in the following years productivity improved more rapidly than before.

Abbott and Doucouliagos (2009) explored the efficiency of Australian and New Zealand public universities in order to investigate the impact of competition for students from overseas on efficiency. Output distance functions are estimated using panel data for the period 1995–2002 for Australia and 1997–2003 for New Zealand. The results show that competition for overseas students has led to increased efficiency in Australian universities. However, competition for overseas students appears to have had no effect on efficiency in New Zealand.

Bradley et al. (2010) used data for nearly 200 further education providers in England to investigate the level of efficiency and change in productivity over the period 1999–2003. Using data envelopment analysis they found that the mean provider efficiency varies between 83 and 90 % over the period. Productivity change over the period was around 12 %, and this comprised 8 % technology change and 4 % technical efficiency change. A multivariate analysis is therefore performed, which shows that, in general, student-related variables such as gender, ethnic and age mix are more important than staff-related variables in determining efficiency levels. The local unemployment rate also has an effect on provider efficiency. The policy implications of the results are that further education providers should implement strategies to improve the completion and achievement rates of white males, and should also offer increased administrative support to teachers.

Given the fact that due to tight public budget constraints, the efficiency of publicly financed universities in Germany is receiving increasing attention in the academic as well as in the public discourse, Pohl and Kempkes (2010) analyzed the efficiency of 72 public German universities for the years 1998–2003, applying DEA and stochastic frontier analysis. Contrary to earlier studies, they account for the faculty composition of universities which proves to be an essential element in the efficiency of higher education. Their main finding is that East German universities have performed better in total factor productivity change compared to those in West Germany. However, when looking at mean efficiency scores over the sample period, West German universities still appear at the top end of relative efficiency outcomes.

Johnes et al. (2010) investigates efficiency levels by subject of study within further education (FE) colleges. Mean overall technical efficiency is found to vary from 75 to 86 % in the worst- and best-performing subject areas, respectively.

Statistical analysis of efficiency reveals that, while student and teacher composition and regional characteristics affect efficiency in each subject, the strength of these effects can vary by subject. This has the clear policy implication that strategies to improve efficiency in English FE must be devised and operated at subject rather than provider level.

Since in a context of financial stringency like that characterizing the current economic landscape in Portugal and in several other countries, accountability and efficiency questions gain an additional relevance in the higher education sector, Cunha and Rocha (2012) applied DEA techniques to evaluate the comparative efficiency of public higher education institutions in Portugal. The analysis is performed for three separate groups: public universities, public polytechnics and the several faculties of University of Porto. The results suggest that a great portion of institutions may be working inefficiently, contributing to a significant waste of resources.

Foltz et al. (2012) investigated the determinants of TE and technological progress at US research universities. It relies on a unique panel data set of multiple outputs and inputs from 92 universities covering the period 1981–1998. Over that time span, US universities experienced large increases in industry funding and in academic patenting activity. In this context, the directional distance function and a nonparametric representation of the underlying production technology are combined to obtain estimates of productivity growth and TE. An econometric analysis is then presented to examine the determinants of TE and the rate of technological progress. The results show how changes in funding sources for US research universities affects research performance.

Wolszczak-Derlac (2014) used DEA to evaluate the relative efficiency of 500 higher education institutions (HEIs) in ten European countries and the U.S. for the period between 2000 and 2010. Efficiency scores are determined using different input-output sets (inputs: total revenue, academic staff, administration staff, total number of students; outputs: total number of publications, number of scientific articles, graduates) and considering different frontiers: global frontiers (all HEIs pooled together) and a regional frontier (Europe and the U.S. having their own frontiers). Changes in total factor productivity are assessed by means of the Malmquist index and are decomposed into pure efficiency changes and frontier shifts. Also investigated are the external factors affecting the degree of HEI inefficiency, e.g. institutional settings (size and department composition), location, funding structure (using two-stage DEA analysis following the bootstrap procedure proposed by Simar and Wilson 2007). Specifically, it is found that the role of the university funding structure in HEI technical efficiency is different in Europe and in the U.S. Increased government funding is associated with an increase in inefficiency only in the case of European units, while the share of funds from tuition fees decreases the efficiency of American public institutions but relates to efficiency improvements in European universities.

Jonhes (2014) explored the issue of efficiency in English higher education using DEA and stochastic frontier analysis to estimate an output distance function (which incorporates measures of both quantity and quality of teaching and research inputs and outputs) over a 13-year period. The study compares the efficiency estimates

derived from various estimation methods, and uses the results to provide guidance to researchers, managers and policymakers on undertaking efficiency studies. The length of the study under consideration allows a preliminary statistical investigation of the effects on efficiency of merger activity in higher education.

Barra and Zotti (2016) applied data envelopment analysis (DEA) to assess technical efficiency in a big public university. Particular attention has been paid to two main activities, teaching and research, and on two large groups, the Science and Technology (ST) sector and the Humanity and Social Science (HSS) sector. The findings, based to data from 2005 to 2009, suggest that the ST sector is more efficient in terms of quality of research than the HSS sector that instead achieves higher efficiency in teaching activities. A bootstrap technique is also used to provide confidence intervals for efficiency scores and to obtain bias-corrected estimates. The Malmquist index is calculated to measure changes in productivity.

### Technical Efficiency Analysis for the Indian Education Sector

Kingdon (1996) presented empirical evidence on the relative quality and efficiency of private and government-funded schools in urban India, using data from Uttar Pradesh. The results suggest that standardizing for home background and controlling for sample selectivity greatly reduces the raw average achievement advantage of private school students over public school students, but does not wipe it out. Private schools' standardized achievement advantage (or better quality) is complemented by their lower unit costs to enable them to be more efficient. The results support much of the existing evidence on the relative efficiency of private and public schools.

Tyagi (2009) assessed the technical efficiency and efficiency differences among 348 elementary schools of Uttar Pradesh state in India by using DEA.

Sankar (2007) considered efficiency of *elementary education as a whole* for different states of India considering two points of time: the mid-1990s and 2004–05 but not for primary and upper primary level of education separately. In Sankar (2007) the factors that contribute to the “efficiency scores” largely remain unexplained—However, some of the regressions showed the role of density of population, a proxy to look at concentration factor and hence the scope for economies of scales to operate, as significant.

Sengupta and Pal (2010) explained the efficiency *primary education sector in India* using DISE statistics only for the year 2005–06. They identified some basic aspects of education: deprivation aspects, social aspects, policy aspects. The country has been divided into five zones: Northern, North-eastern, Eastern, Western and Southern districts respectively. Using Anand and Sen (1997) formula of Human Poverty Index (HPI) they derived Grand Poverty Index comprising of various poverty indicators of education system in India and tried to relate these with the efficiency score in DEA. The result of their study indicates that poverty indicators have negative impacts on efficiency, whereas social and policy indicators are not significantly related to the efficiency improvement.

Sengupta and Pal (2012) explained the efficiency of only primary education sector of Burdwan District of West Bengal, corresponding to a single year 2006.

Purohit (2015). Rajasthan being India's largest state comprising 10.4 % of India's total area is located on the western side of the country. The state is divided into 33 districts. Over the 1990s and early 2000s, enrolment rates at the primary level were rising and gender gap converging, though female enrolment rate is still to catch up with that of male. There also exist considerable differential across districts in the State. As per survey in 2012, overall literacy varies from 55.58 % (Jalore) to 77.48 % (in Kota). In this paper, considering the district level variations in literacy and other pertinent socio-economic variables he explores whether efficiency in education in district level enrolments is merely a reflection of the other conditions or is it owing to lack of efficient utilization of available educational input variables. Thus he estimates district level efficiency in enrolments at primary and upper-primary levels, in government and private schools, in Rajasthan and look into reasons for their differentials. Using data for the period 2008–2012 and applying stochastic frontier analysis their results indicate that a strong role is being played by economic development parameters like income and urbanization. And simultaneously direct educational interventions seem to play a positive role in enhancing enrolments at different levels. Therefore an education policy should capture district specific gaps to strengthen the outcomes. This may thus necessitate more information at district level both in terms of educational and economic parameters and this information gap needs to be overcome through planning process.

## 2.3 Connections of Present Book with Existing Literature

*The perusal of the literature suggests the following gaps in the existing literature relating to the efficiency of elementary education sector in India. The present book attempts to overcome these above limitations and contributes to the literature in the following directions.*

*First of all*, in contrast to existing studies the book does not assume a common frontier for all the Indian states and the union territories. As explained in Chap. 1 it is difficult to assume a common frontier for all the states and union territories in India as not all of them operate under same economic and fiscal condition. Rather, the book constructs two group frontiers: (i) for states only with GCS and (ii) for the states under SCS and UT. The book carries out the group frontier and Meta frontier analysis. The Meta frontier defines the frontier corresponding to all the 35 states and union territories taken together. In particular, Technology Closeness Ratio (TCR) measuring whether the maximum output producible from an input bundle by a school within a group is *as high as* what could be produced if the school could choose to locate anywhere in India is computed. TCR shows the divergence of the group frontiers from the Meta frontiers, to what extent group frontiers are close to the Meta frontiers. Such a computation of TCR will help us to identify whether

maximum output producible by SCS is higher or lower than that could be produced under GCS, given the resources.

Secondly, the book estimates technical efficiency score of both primary and upper primary level of education for the above two groups and compares the performance of efficiency score of primary and secondary level of education for six successive years from 2005–06 to 2010–11. *While estimating technical efficiency score it takes into account both quantities as well as quality aspects of outputs and inputs. The earlier Indian studies dealing with interstate variation of technical efficiency score did not consider the quality aspects.*

Thirdly, the book measures the extent of underutilization of different inputs, for different States and union territories of India, both for primary and upper primary level of education, *the estimates of which are still lacking in the literature.*

Finally, while finding out the determinants of efficiency, it intends to take into account (i) some factors from poor infrastructure to see whether poor infrastructure inhibit the achievement of TE, (ii) some factors from favorable infrastructure to see whether favorable infrastructure induces the achievement of TE, (iii) some social indicators to investigate whether inclusion of the backward classes into the education system increases TE, (iv) some policy variables to test whether provision of more public facilities increases TE and also (v) some state level macro aggregates like per-capita net State domestic product, income inequality, and number of persons lying below the poverty line to see to what extent the general environment of the state matters in explaining TE. Also, rather than using a composite index the present book attempts to find out the individual effect of the different explanatory variables. The earlier result that social and policy indicators are not significantly related to the efficiency improvement may be due to the use of composite index. It is quite possible that some of the individual factors comprising of the composite variables are significant while the others are not. Separate regression is carried out for primary and upper primary level. *The relative sensitivity of the central-grant in explaining the efficiency performance of primary and upper-primary education of both GCS and SCS&U is estimated, which can be used for judging the efficacy of central grant in promoting technical efficiency of these two groups and there is paucity of such estimation.*

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