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ELEMENTARY EDUCATION OUTCOME EFFICIENCY OF INDIAN STATES: A RAY FRONTIER APPROACH

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Abstract

This study uses the generalized stochastic frontier approach to estimate the technical efficiency of Indian States in providing elementary education from 2009-10 to 2018-19. Mean efficiency was estimated at 85 percent and it varied between 67 percent to 97 percent. Considerable inter- state disparity is observed in elementary education outcome and 96 percent of the disparity is explained by inefficiency. Kerala is the most efficient State followed by Maharashtra and Himachal Pradesh. Arunachal Pradesh is the least efficient state, followed by Sikkim and Tripura. Efficiency estimates were observed to change across States over the study period. Proportion of government schools, rural population and Schedule caste and Schedule Tribe children are the major determinants of inefficiency. Finally, the study identifies best practices and helps in separating the resource poor States from the inefficient ones. The study is useful for designing public policy that would help in removing regional imbalances in elementary education outcome.

Keywords: *technical efficiency, public expenditure, elementary education outcome, stochastic frontier analysis, Ray frontier.*
JEL Codes: *C14, D24, I21, I28, H52*

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INTRODUCTION

India enacted the Right to Education Act, 2009 to ensure universal access to elementary education for every child[1]. To achieve this goal, both the Centre and the State Governments allocate considerable public resources to the sector. However, the primary responsibility for providing public education lies with the State governments, which contribute around 82 percent of the total public expenditure on elementary education. Despite these efforts, as of 2020-21, only 11 out of 28 States had achieved universalized elementary schooling. Failure of the States to ensure quality and inclusive schooling is often attributed to resource scarcity. However, additional public expenditure cannot be justified if States are inefficient in resource management. The National Education Policy, 2020 too emphasised on the need for resources efficiency and outcome maximisation in the education sector (Government of India [GOI], 2020).

Preliminary analysis of elementary education (EE) outcomes and public spending proves that inefficiency is a matter of concern in several States. For example, in 2020-21 Tripura universalized schooling by spending ₹22,537 per student per annum (pspa), whereas Mizoram spent ₹66,954 pspa to achieve it. Similar, in 2020-21, Arunachal Pradesh had the lowest retention rate (44.55 percent) despite spending ₹71,405 pspa. Whereas Kerala attained a 100 percent retention rate by spending only ₹23364 pspa. Further, the National Achievement Survey 2021 revealed that Bihar, Uttar Pradesh, Chhattisgarh, Assam, Meghalaya, Telangana, and Andhra Pradesh scored significantly below the national average in all subjects (GOI, 2021). While, Bihar, Assam, and Meghalaya had lower spending on EE, the other mentioned States had moderate spending. Despite having the highest expenditure (₹97,174 pspa in 2020-21), Sikkim's performance was below the national average in social science and mathematics, and it had a retention rate of 92 percent.

[1] Elementary schooling / Elementary education is defined as education from grade 1 to 8. Alternative nomenclature can be primary education.

Against this background, this paper measures the technical efficiency of 28 Indian States[2] from 2009-10 to 2018-19, in generating EE outcomes using the generalized stochastic frontier approach (GSFA), also known as the Ray Frontier Approach. It also analyzes the determinants / sources of technical inefficiency in these States.

Technical Efficiency (TE) reflects the ability of a decision-making unit (in this case the State Governments) to obtain maximum possible output from a given set of inputs and technology. In simple term, it refers to the ratio between actual output produced and maximum possible (potential) output. There are three popular methodologies in the literature to measure the education outcome efficiency, namely 1. DEA or Data Envelopment Analysis (non- parametric approach), which is a linear programming based technique that maximizes the objective function (output oriented approach) subject to given inputs and output constraints; 2. SFA or Stochastic Frontier Analysis (parametric approach), which involves econometric modelling of the frontier production function; and 3. Hybrid Approach, which uses locally weighted scatter plot smoothing to estimate the frontier and Mahanalobis matching to estimate the TE scores (Wagstaff and Wang, 2011 and Grigoli, 2014). Very few empirical studies use the Hybrid approach, whereas the first two approaches are widely used in the literature.

Various international studies have examined the education outcome efficiency at national and subnational levels. D'Elia and Ferro (2021) examined the efficiency of public higher education in Argentina from 2005 to 2013. Guarini *et. al.* (2020) studied the impact of social capital and quality of government on educational resource efficiency across 17 regions of Italy. Campoli *et. al.* (2019) measured the efficiency of Brazilian Federative units in providing education. Yotova and Stefanova (2017) studied the efficiency of 9 European Union member countries in producing tertiary education outcomes such as employment, social

[2] Former State of Jammu and Kashmir is included, and Andhra Pradesh and Telangana is taken together.

inclusion, and standard level of income. Dufrechou (2016) used the Barro Lee dataset to compare efficiency of 11 Latin American countries with 24 high income countries, from 1970 to 2010. Titus and Eagan (2016) compared the efficiency of public and private higher education institutions in the US. Sirait (2015) studied the efficiency in education expenditure across 33 provinces in Indonesia.

Learning outcome data provided by the Program for International Student Assessment (PISA) Surveys has been used in several cross-country and country specific studies. Delprato and Antequera (2021) used the PISA Survey data to compared the efficiency of public and private schools in four Latin American Countries, namely Ecuador, Guatemala, Honduras and Paraguay. Salas-Velasco (2020) used it to study the efficiency of public schools in Spain. Arias Ciro and Torres García (2018) measured the efficiency of 37 developed and developing countries in providing secondary education. Other studies include, Šonje, Deskar-Škrbić, and Šonje (2018) that compared Croatia to 11 other European Union countries; Salazar Cuéllar (2014) compared 15 Latin American countries; Agasisti (2014) measured efficiency across 20 European Union member countries; Thieme, Giménez, and Prior (2012) that studied 54 countries; and Afonso and Aubyn (2005) that studied 25 countries in 2003.

In the Indian context, only a few studies emerge on the topic. Most of the studies have examined the outcome efficiency at the school level/ institution level (Kulshreshtha and Nayak, 2015; Das and Das, 2014; Sunitha and Duraisamy, 2012; Tyagi *et. al.*, 2009; Kington, 1996). Purohit (2015) and Ghose and Bhanja (2014) have estimated the district level efficiency in enrolments at primary and upper-primary levels, in Rajasthan and West Bengal respectively. Studies analysing the education outcome efficiency of Indian States are very few. Mohanty and Bhanumurthy (2020) and Purohit (2014) have examined the efficiency of the entire education sector across Indian States. Gourishankar and Lokachari (2012) have analysed the educational development efficiencies of the Indian States and Union Territories. Dutta (2012) used DEA to measure the elementary education outcome efficiency of Indian States for the year 2007-08. The study considered enrolment rates and completion rates in primary and upper primary school as output variables, and distance from school and pupil teacher ratio as inputs. Ghose (2017), too used DEA to estimate the technical efficiency score at both primary and upper primary level of education for all the States and Union Territories from 2005-06 to 2010-11. Purohit (2016) conducted a similar study in urban areas of 19 States for 2012-13.

Most studies have preferred the DEA over the SFA method as the former allows for a multi- output, multi- input framework. However, the DEA methodology suffers from various limitations: (1) they are highly sensitive to variable selection; (2) subject to small sample bias; and (3) produces biased estimates in the presence of statistical noise. Hence it cannot be used for policy suggestions. On the other hand, the SFA is relatively stable and a superior methodology (Sutherland *et. al.*, 2009; Rassouli-Currier, 2007; Coelli *et. al.*, 2005). But it either considers a single output at a time or an aggregate index of many outputs.

Given that the education production process employs multiple inputs that simultaneously generate multiple outputs, few empirical studies have used a multi-input multi-output stochastic frontier approach to measure efficiency in education. Perelman and Santin (2011) estimated a stochastic output distance functions to measure the technical efficiency of Spanish students. The study considered two outputs: mathematics and reading test scores, and multiple inputs such as school inputs, student background and peer-group characteristics. Miningou (2019) constructed the Learning Adjusted Years of Schooling, an index composed of years of schooling and harmonized test scores to measure the education outcome and examined the efficiency of 130 countries in providing education. Melo-Becerra *et. al.* (2020) estimated a multiple inputs and multiple outputs production function to analyse the efficiency of Columbian municipalities in providing public education in the year 2008 and 2013. Miningou and Vierstraete (2017) used the GSFA model developed by Löthgren (1997) to estimate the efficiency of the 45 provinces of Burkina Faso in providing primary education.

Past empirical studies also identify the determinants of technical efficiency/ inefficiency in education. Income/ Gross Domestic Product (or indicators of standard of living), income inequality, poverty, literacy rate/ standard of education, teacher's degree and experience, grants for teachers' training, student- classroom ratio, student – teacher ratio, schooling infrastructure, unemployment rate, social capital, gender parity index, density of population, children belonging to minority/ disadvantaged sections of the society, corruption and quality of governance indicators, and level of urbanisation (alternatively, rural population) are factors that are expected to impact education outcome efficiency of the DMUs (Mohanty and Bhanumurthy 2020; Dufrechou 2016; Purohit, 2016; Dutta, 2012; Chakraborty, 2009; Sankar, 2007; Jayasuriya and Wodon, 2007; Pereira and Moreira, 2007; Rassouli-Currier, 2007; Herrera and Pang, 2005; Wodon and Jayasuriya, 2003; Kang and Greene, 2002).

This paper contributes to the existing literature in several ways. First, it uses the latest data to estimate the TE of Indian States in generating the outcome of elementary education. Second, it examines the change in TE over the span of 10 years (the existing studies are cross-sectional in nature). Third, it is the first paper to apply the generalized stochastic frontier model to examine the efficiency in the elementary education sector in India. This methodology does away with the limitations of the DEA and the standard SFA and therefore provides a more robust and accurate estimation of TE. Fourth, the study also considers a wider range of explanatory variables. This would provide a deeper understanding on the topic. Fifth, it uses the *Inefficiency Effects Model* developed by Battese and Coelli (1995) to simultaneously estimate the generalized frontier production function and inefficiency function (that identifies the determinants of TE). The previous Indian studies employed the two- stage approach, according to which, TE is estimated in the first stage using DEA/ SFA methodologies and in the second stage the efficiency estimates are used to identify the determinants of TE using censored tobit / OLS. Kumbhakar *et. al.*,(1991); Battese and Coelli (1995); Wang and Schmidt (2002); and Simar and Wilson (2007) proved that the two-step approach produced biased and inefficient estimates. Hence, Battese and Coelli (1995) developed a single stage Maximum Likelihood Estimation (MLE) technique that does away with the limitations of the two-stage procedure[3]. Lastly, the study identifies best practices and can be useful in ensuring that public resources are put to optimal use. The study also helps in segregating the resource poor States from the inefficient ones.

The paper proceeds as follows. The next section discusses the data sources and the rationale for variable selection, and following sections discuss the methodological approach and empirical strategies and empirical results. The final section provides the conclusion and policy implications.

VARIABLE SELECTION AND DATA SOURCE

Production of EE simultaneously leads to the generation of multiple outputs that can be broadly classified into: (1) indicators of access/ quantity- such as retention/ completion rate, enrolment/ attendance rates, etc; and (2) indicators of learning outcomes/ quality- such as standardised test score in maths/ science/ language (Scheerens et. al.*,* 2011; Hanushek, 1979). However, these indicators are not free from limitations. Literature suggests that Retention Rate (RR) is a better and a more comprehensive indicator of access compared to enrolment ratios (UNESCO, 2009). RR is one of the key monitorable targets of the Sustainable Development Goals (UNESCO, 2018). Therefore, RR is selected as the indicator of access.

In India, there are two nation- wide surveys that measure learning outcomes: (1) Annual State of Education Report (ASER) survey; and (2) The National Achievement Survey (NAS) (PRATHAM, 2018; GOI, 2017;

[3] In order to solve the problems pertaining to the two- stage approach, Simar and Wilson (2007) developed the methodology for the Bootstrap DEA for cross -section data.

GOI, 2021). The major differences between ASER and NAS are: (1) ASER conducts a floor test where all children are administered the same test[4] irrespective of age/ grade/ schooling status and the highest level of proficiency in reading and arithmetic is recorded, whereas NAS administers grade- specific tests covering various subjects. (2) ASER survey is comparable across time, whereas NAS 2017 is not comparable with the earlier rounds due to methodological changes. NAS 2021 cannot be compared to NAS 2017, without considering the impact of Covid -19[5]. (3) Johnson and Parrado (2021) warned about the presence of severe unexplained biases in the NAS data and suggested that it should not be used for inter-State comparisons. This study chooses ASER over NAS, as ASER allows for efficiency estimation over time and it is more reliable. Percentage of children in the age group 11- 13 years who passed the basic reading test/ arithmetic test were considered to have reading/ arithmetic ability.

This study considered ***RR***, ***reading ability and arithmetic ability*** (at elementary level) as the outputs of EE production process. Input variables chosen based on literature review are: real public expenditure per student, real GSDP per capita, number of teachers per 35 students, number of schools per lakh child population, and several schooling infrastructure variables. The infrastructure variables include: percentage of schools that have functional girls' toilet, electricity, computer, drinking water sources, library, and roads. Facilities such as provision of Mid- day meals and medical check-ups were also considered. Teachers having Bachelor's in Education/ equivalent degree may produce better learning outcomes. Therefore, proportion of professionally qualified teachers is also considered. However, data for all the input variables are not consistently available for all the years. Data on road, library and medical check-up are available from 2012-13 to 2020-21. Data on the

[4] The highest level of reading test is the ability to read grade 2 level text (a story). The highest level of arithmetic test is the ability to solve a 3- digit by 1- digit division question.

[5] Compared to NAS 2017, the learning outcomes have declined in all grades and all subjects in NAS 2021. This may be due to the impact of Covid- 19.

proportion of professionally qualified teachers is missing for the year 2009-10 and 2010-11. Several of the input variables were dropped during the estimation process and only relevant variables were included in the final model.

Variables in the Inefficiency Model include: literacy rate, proportion of rural population, proportion of government schools, and the proportion of Schedule Caste (SC)/ Schedule Tribe (ST) children, and percentage of teachers having regular nature of appointment.

Data was compiled from various secondary sources. Expenditure data is taken from the Finance Account of States, Comptroller and Auditor General of India [CAG] (2022). Data on retention rate and schooling infrastructure variables are taken from Unified District Information System on School Education [UDISE] (2015, 2022). Literacy rate and rural population has been projected based on census data (GOI 2001, 2011). Data on provision of Mid- Day meals is compiled from Annual Work Plan and Budget documents of the States (GOI, 2022a). Data on population in elementary schooling age is taken from the GOI (2022b). GSDP data were compiled from National Statistical Office (2022). Data on learning outcome is taken from ASER Survey, PRATHAM (2022).

METHODOLOGY AND EMPIRICAL STRATEGIES

The SFA model developed by Aigner, Lovell, and Schmidt (1977) and Meeusen, and van den Broeck (1977) is an extension of a conventional production function. While the conventional production function assumes that all producers all fully efficient and all deviations from the production possibility frontier are solely due to random shocks, the SFA specifies a frontier production function where the regression error term can be decomposed into statistical noise and a measure of inefficiency. The SFA model can be represented as:

$Y = f(.)e^{-u} e^{v} = f(.) e^{\varepsilon}$, where Y is output, v is the stochastic error term, u is the gap between actual and potential output, and ε is the composite error term (v-u). The inefficiency term (u) is non-negative and is assumed to follow either a half normal / truncated normal / exponential / gamma distribution. SFA models are estimated using MLE method.

Over the period of time, several SFA models have been developed, for example, Pitt and Lee (1981) developed a time invariant model SFA model for panel data and assumed that the technical inefficiency term (u) follows a half normal distribution. Battese and Coelli (1988) developed a time invariant model that was a more generalized version of the Pitt and Lee (1981), assuming that "u" follows a truncated normal distribution. Schmidt and Sickles (1984) and Cornwell (1990) used the conventional random effects and fixed effects models for panel data to estimate production frontier and time invariant efficiency and made no assumptions regarding the distribution of "u". Lee and Schmidt (1993) developed a time varying model with no distributional assumption of "u". While the Cornwell *et. al.* (1990) model was found to be more flexible, Lee and Schmidt (1993) model was more parsimonious and less flexible because it used time dummies. Further, Kumbhakar (1990) and Battese Coelli (1992) developed two alternative models to measure time varying efficiency.

All the aforementioned methods employ a two- step approach. After estimating the efficiency in the first stage, the TE scores are regressed on various factors to identify the major determinants of efficiency in the second stage. But, estimating the model in two stages is inconsistent in its assumptions regarding the independence of the inefficiency effects. Wang and Schmidt (2002) and Simar and Wilson (2007) proved that the two-step approach produced biased and inefficient estimates. Battese and Coelli (1995) developed the ***Inefficiency Effects Model*** that simultaneously estimates the frontier production function and the inefficiency function, hence solving the problems of the two– step approach.

The basic SFA models estimate an equation with one output (dependent variable) and several inputs (independent variable). Löthgren

(1997, 2000) generalized the single output SFA model into a multi- output Ray Frontier production function model. Since this study considers RR and learning outcomes as multiple outputs, it uses the GSFA (Ray Production Frontier) framework in the context of ***Inefficiency Effects Model***.

The Ray Production Frontier constructs an output measure/ output norm based on the production possibility frontier that represents the relationship among the outputs. The polar co-ordinate angles between the output vectors play an important role in determining the relationship between the output norm and the inputs. For a given output mix and input level, the generalized production function gives the maximum Euclidean norm of the output vector that is attainable given the technology. Formally, for a production technology with multiple inputs that are used to produce multiple outputs, the generalized production function represents the output vector in polar coordinate form as:

$Y = \iota . f(\theta)$ (1)

where, $\iota = ||Y_{it}|| = (Y_1^2 + Y_2^2 + Y_3^2)^{1/2}$ (2)

Here Y_1, Y_2, and Y_3 represent the three output variables namely, retention rate, arithmetic ability and reading ability respectively. $||Y_{it}||$ is the Euclidean norm of the outputs, and

$f(\theta) = Y / ||Y_{it}||$ represents the transformation function of the polar coordinate angles θ to the output mix vector. Further, the polar coordinate angles θ are obtained recursively from the inverse transformation of $f^{-1} (Y / ||Y_{it}||)$ as:

$\theta_i = cos^{-1} (Y_i / ||Y_{it}|| . \prod_{j=0}^{i=1} sin\, \theta_j)$, where $i = 1, 2, 3$ (3)

The first polar coordinate angle is : $\theta_1 = cos^{-1} (Y_1 / \iota)$. θ_1 is further used to compute the second angle: $\theta_2 = cos^{-1} (Y_2 / \iota . sin\, \theta_1)$.

The frontier production function can be specified as:

$$\iota = ||Y_{it}|| = f(X,\theta)\ exp\ (v_{it} - u_{it}) \qquad (4)$$

By taking logarithms of equation (4), we can obtain the generalized SFA model for panel data as:

$$ln\ ||Y_{it}|| = \beta_0 + \Sigma_j\ \beta_j\ ln\ X_{jit} + \lambda_1\ ln\ \theta_{1it} + \lambda_2\ ln\ \theta_{2it} + v_{it} - u_{it} \qquad (5)$$

where, $||Y_{it}||$ is the output norm as defined in equation (2); 'i' is the number of States; 't' is the year; X_{jit} are input variables and θ_1 and θ_2 are the two polar coordinate angles; v_{it} is the stochastic error term, $v_{it} \sim$ iid N (0, σ_v^2); and u_{it} is the inefficiency component. Let $v_{it} - u_{it} = \varepsilon_{it}$ (a composite error term). All the variables in equation (5) are in log form. Equation (5) is then estimated using the Inefficiency Effects Model developed by Battese and Coelli (1995).

According to Battese and Coelli (1995), u_{it} follows a truncated normal distribution and time varying mean, $u_{it} \sim$ iid N+ (m_{it} , σ_u^2). Technical inefficiency term (m_{it}) itself depends on a set of environmental factors that impact TE. The Inefficiency Model can and can be written as:

$$m_{it} = \delta\ Z_{it} \qquad (6)$$

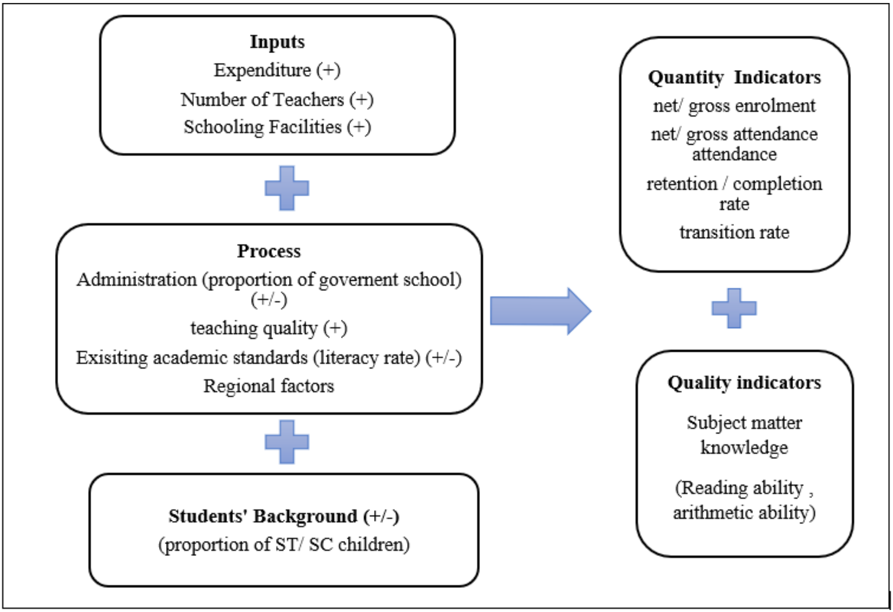
where, Z_{it} is the vector of variables that influence the technical efficiency of the decision-making units (States). Variables used in equation (6) are literacy rate, rural population, and proportion of government schools. As suggested in Jondrow et. al., (1988) and Battese and Coelli (1988), we can predict the TEs as the expectation of the truncated error term (u) conditional on composed error term (ε), i.e., $TE = E\ [exp(-u_{it})\ |\ \varepsilon_{it}]$.

MLE is used for the simultaneous estimation of the parameters in the Ray frontier production model and in the technical inefficiency model. The likelihood function is parameterized in terms of the variances in the model and the variance ratio $\gamma = \sigma_u^2 / \sigma^2$ (where σ^2 is the sum of two variances in the model σ_u^2 and σ_v^2). Gamma (γ) shows the relative magnitude of the technical inefficiency variance to total variance in the model. It lies between 0 and 1. If γ is zero, then the variance of the inefficiency effect is zero and the model is reduced to a traditional mean response function in which the variables in Z are included in the production function. In this case, the parameters δ are not identified. One can test the null hypothesis that $\gamma = \delta_0 =..= \delta_m = 0$ using the generalized likelihood ratio test statistics[6] that follows a mixed χ^2 distribution, with degrees of freedom equal to the number of restrictions imposed. Critical values of the mixed χ^2 distribution are obtained from Kode and Palm (1986).

Conventionally, the SFA models are an extension of the Cobb-Douglas (CD) production function. However, CD production functions are quite restrictive as they assume constant elasticity of substitution. Several studies also use the trans-log production function because it does not impose restrictions on scale elasticities, i.e., it is much more flexible and it allows the production function to be concave (Rassouli-Currier, 2007; Sutherland, 2009; Arshad, 2012; Miningou, 2019). However, it often causes multicollinearity problem due to the presence of several input interaction terms. A few studies have also used quadratic specifications of the education frontier production function (Peirra and Moreira, 2007; Perelman and Santin, 2011; Kang and Greene, 2002). The best practice is to estimate several specifications and choose the most relevant model based on Likelihood Ratio test and Information Criterions (D'Elia and Ferro, 2021; Guarini *et. al.*, 2020; Koku, 2015; Chakraborty, 2009). Since there are only 216 observations in the database used in this study, a functional form that requires estimation of fewer parameters, is more desirable. Figure 1 illustrates the conceptual framework for the study.

[6] LR test statistic = -2 [$L(H_R) - L(H_{UR})$]; where, $L(H_U)$ and $L(H_{UR})$ represent the log-likelihood values computed from the restricted model (OLS) and the unrestricted model (SFA) respectively.

Figure 1: Conceptual Framework for Analysing the Efficiency of Indian States in Generating Elementary Education Outcomes



Source: Author's Illustration

EMPIRICAL RESULTS

Descriptive Statistics

Descriptive data analysis reveal that States have performed relatively better in providing access to elementary schooling than in generating learning. Goa, Haryana, Kerala, and Punjab had 100 percent RR in several years. Out of the three outcomes, Arithmetic ability of the students is the weakest. Only 10 percent of the students in Meghalaya could qualify the arithmetic test in 2018-19. In 2009-10, RR in Meghalaya was 26 percent (lowest) and it improved to 44 percent in 2018-19. Only 36 percent of the students in Tripura could qualify the reading test in 2009-10, it improved to 55 percent in 2018-19.

Table 1: Descriptive Statistics

Variables	Observations	Mean	Standard Deviation	Min	Max
Retention Rate	216	67.16	20.52	26.06	100.00
Reading Ability	216	65.00	11.27	36.36	92.42
Arithmetic Ability	216	43.27	15.13	10.10	87.45
Real per student expenditure per annum (in ₹)	216	14258	9210	2871	47759
θ_1 (retention rate)	216	0.87	0.15	0.56	1.25
θ_2 (reading ability)	216	1.06	0.12	0.79	1.32
Teachers per 35 students	216	1.85	0.82	0.58	5.92
Percentage of schools having functional drinking water	216	86.90	14.12	31.73	100.00
Percentage of schools having functional girl's toilet	216	77.93	21.07	15.18	100.00
Percentage of children (age 6-13) receiving Mid-day meals	216	61.05	18.58	23.89	100.00
Percentage of schools having Library	134	70.31	27.55	4.98	99.31
Percentage of schools approachable by Roads	161	85.35	15.27	0.00	100.00
Percentage of schools providing medical check-up	134	45.31	26.88	3.50	97.24
Percentage of government schools	216	75.30	13.11	28.80	99.94
Percentage of ST-SC children in child population	216	38.30	23.03	2.21	97.71
Literacy rate	216	77.63	8.26	58.51	98.61
Percentage of rural population	216	68.85	12.36	34.74	90.02
Percentage of teacher's having regular appointment	216	81.42	21.10	16.38	100.00

Source: Author's estimation

Considerable inter- State variation exists in all the input variables. States on an average spent ₹14,258 per student per annum during the study period and the lowest and highest expenditure was made by Bihar and Mizoram respectively. Teacher scarcity can be observed in Bihar, Jharkhand, and Uttar Pradesh whereas, abundance of teachers can be found in Sikkim (teacher per 35 students was 5.92 in 2018). Meghalaya fairs poorly in most of the infrastructure variables. In 2018-19, only 32 percent schools in Meghalaya had functional drinking water facilities (it was 31.73 percent in 2013-14); 8 percent schools had a library (5 percent in 2012-13); and 15 percent schools provided medical check-up facilities (3.5 percent in 2012-13). 28 percent children in Jammu and Kashmir received Mid- day meals in 2018-19 (it was 24 percent in 2016-17). In 2009-10, 15 percent schools in Manipur had girl's toilet, it increased to 67 percent in 2018-19 whereas, it was 99 percent in Goa in 2018-19. Table 1 presents the descriptive statistics of the study variables where the polar coordinate representation of the outputs is presented in addition to the original output variables, key input variables, and variables included in inefficiency model.

Elementary Education Outcome Efficiency and Its Determinants

Table 2 presents the MLE results of the stochastic Ray Frontier function equation 5 and the technical inefficiency model equation 6. The outcome variable used in this exercise is the Euclidian Output norm estimated using equation 2. The Output norm consists of 3 outputs namely, retention rate at elementary level, arithmetic ability and reading ability. Specification (1) includes all the input variables for which data is available from 2009-10 to 2018-19[7] for all the 28 States. Since learning outcome data is not available for all the years, we have an unbalanced panel of 216 observations. Specification (2) only includes the inputs that were significant in Specification (1).

Specification (3) includes additional input variables such as percentage of schools that have a library, that are approachable by road

[7] The latest learning outcome data is available for the year 2018-19.

and that provide medical check-up. Data for these 3 variables are available from 2012-13 to 2018-19, and so Specification 3 consists of an unbalanced panel of 134 observations. Specification 3 gives additional information about the elementary education production frontier. However, Specification (2) has been chosen over Specification (3) to estimate the TE scores because the former contains a greater number of observations.

Along with the input variables, the two polar coordinate angles (θ_1 and θ_2) have also been included as independent variables as per the methodology explained in Section 2. Both the polar coordinate angles (θ_1 and θ_2) are positive and significant in all the 3 specifications, indicating that the frontier output norm depends on the combinations of the three outputs that are produced with the given resources (inputs) and technology. That is, the output mix has a significant effect on the frontier output norm for a given input vector.

Per student elementary education expenditure (real) has a positive and significant impact on the education output in all the 3 specifications. However, its squared term, i.e., the square of per student expenditure is negative and significant. This implies that additional units of expenditure have a lower impact on outcome compared to the previous units of expenditure and the relationship between outcome and expenditure eventually wears off after a certain point. The findings suggest that States with lower expenditure on public education are likely to experience greater improvements in outcomes with additional public spending compared to States with higher expenditure levels.

All the other inputs variables have positive input elasticities (or coefficients) as expected. These are in accordance with the input monotonicity property. Interestingly, many of them are statistically significant. Results indicate that if there are more teachers per 35 students[8], delivery of service tends to improve which leads to better

[8] According to Right to Education Act Norms, the ideal pupil – teacher ratio is 35.

learning outcomes and higher retention rate. Availability of drinking water also has a significantly positive impact on education outcome. However, percentage of schools having girl's toilet and percentage of children receiving mid- day meals were not significant. Hence these variables have been dropped in Specification 2. Findings from Specification 3 are similar to that from Specification 2 and the three additional variables (namely, library, road and medical check-up), also have a significant and positive impact on education outcome. These results suggest that better schooling infrastructure leads to better learning and less drop-outs.

In all the three specifications, both σ^2 and γ are statistically significant at 1 percent, indicating the validity of the GSFA model and confirming the inefficiency of States in producing elementary education outcomes. Alternatively, the generalized likelihood ratio test (mixed χ^2) rejects the null hypothesis that $\gamma = \delta_0 = \ldots = \delta_m = 0$, implying that the parameters of Z variables (in equation 6), are identified statistically and the technical inefficiency model is valid. In specification 2, the estimated value of γ (i.e., the proportion of total variation due to variation in TE) indicates that 96.36 percent of the difference between actual and potential outputs is due to technically inefficient performance of Indian States.

The Inefficiency Model identifies the determinants of technical inefficiency. Estimates show that the proportion of SC-ST children have a positive and significant impact on technical inefficiency. Government schools are also positively and significantly associated with technical inefficiency. States that have more of rural population are relatively more inefficient. Literary rate is not a significant determinant of technical inefficiency. Technical efficiency improves when teachers are hired as regular staff instead of having contractual/ part- time appointments. However, this variable is not significant in Model (2).

Table 2: Maximum Likelihood Estimation of the Generalized Stochastic Frontier Models and Inefficiency Function

Dependent Variable: log of 3 output norm (retention rate, reading scores and arithmetic scores)

VARIABLES	All variables (2009-10 to 2018-19)	Final Model (all significant in 1)	ncluding library road and medical check-up
	(1)	(2)	(3)
Frontier Production Function			
log of real per student expenditure	0.5586*	0.6998**	0.6352*
	(0.2972)	(0.2892)	(0.3758)
Square of log of real per student expenditure	-0.0289*	-0.0365**	-0.0343*
	(0.0158)	(0.0153)	(0.0197)
log of theta 1 (retention rate)	1.7961***	1.7913***	1.6397***
	(0.1433)	(0.1427)	(0.2047)
log of theta 2 (reading score)	3.1245***	3.1161***	3.0072***
	(0.2303)	(0.2359)	(0.3687)
log of teachers per 35 students	0.1107***	0.1133***	0.1556***
	(0.0277)	(0.0280)	(0.0297)
log of % of schools having functional drinking water	0.3336***	0.3402***	0.1391***
	(0.0396)	(0.0367)	(0.0455)
log of % of schools having functional girl's toilet	0.0194		
	(0.0236)		
log of % of children in age 6-13 receiving mid-day meals	0.0347		
	(0.0299)		
log of % of schools having library			0.0641***
			(0.0228)
log of % of schools approachable by roads			0.0394***
			(0.0132)
log of% of schools providing medical check-up			0.0315**
			(0.0152)
Constant	0.4287	-0.0252	0.6584
	(1.3840)	(1.3739)	(1.7820)
Gamma (γ)	96.75***	96.36***	97.93***
Sigma Square (σ^2)	0.0417***	0.0397***	0.0351**

Inefficiency model			
log of % of government schools	0.3467*	0.2881*	0.8068**
	(0.1933)	(0.1712)	(0.3402)
log of % of ST-SC children in child population	0.2258***	0.2167***	
	(0.0801)	(0.0755)	
log of literacy rate	0.1021		
	(0.3066)		
log of rural population	0.4699**	0.4588**	
	(0.2145)	(0.1929)	
log of % of teacher's having regular appointment	-0.0719		-0.2070**
	(0.0645)		(0.0905)
Constant	-4.4393*	-3.9591***	-2.6173*
	(2.4500)	(1.3723)	(1.3781)
Log Likelihood	169.3198	167.776	120.7873
Number of Iterations	23	19	21
LR- test Statistic (mixed χ^2)	72.5266	72.8262	56.3004
Observations	216	216	134
Number of States	28	28	28

Source: Author's Estimation
Note: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3 provides the technical efficiency scores (TE) and the relative ranking of States over the years. Mean Efficiency of States fluctuated between 83 percent to 89 percent during the study period. It was 83.30 percent in 2009-10, it increased to 88.66 percent in 2013-14, and it was recorded at 84.49 percent in 2018-19. The overall mean efficiency averaged at 85.64 percent, indicating that, on average, Indian States achieved approximately 85 percent of their potential outputs, leaving around 15 percent unrealized. TE of States varied between 67 percent to 97 percent. Based on the overall (mean) efficiency scores, Kerala is the most efficient State followed by Maharashtra and Himachal Pradesh. Whereas, Arunachal Pradesh is the least efficient State, followed by Sikkim and Tripura. In 2018-19, Kerala, Maharashtra, and Himachal Pradesh remained the three most efficient States, whereas the least efficient States were Assam, Jammu and Kashmir and Jharkhand.

Efficiency of the individual States have changed considerably over the period of study. While TE has improved in States like Uttar Pradesh, Gujarat, Haryana, Himachal Pradesh, Meghalaya, and Mizoram, it has declined in Assam, Bihar, Jharkhand, and Madhya Pradesh.

Table 3: Technical Efficiency estimates, Relative Ranks and Mean Efficiency of States based on the Generalized Stochastic Frontier Model (Specification 2)

States	2009-10	2010-11	2011-12	2012-13	2013-14	2014-15	2016-17	2018-19	Mean
Andhra and Telangana	87.10	90.19	90.28	89.06	92.74	88.92			89.72
	(13)	(15)	(10)	(11)	(14)	(17)			(12)
Arunachal Pradesh	80.03	59.53	69.12	79.71		61.20	54.53	70.01	67.73
	(20)	(26)	(26)	(19)		(28)	(26)	(23)	(28)
Assam	83.04	82.61	73.59	72.55	70.91	71.30	75.00	64.88	74.24
	(16)	(23)	(25)	(25)	(25)	(26)	(22)	(26)	(25)
Bihar	91.53	94.79	92.74	81.80	84.31	92.46	80.65	75.16	86.68
	(10)	(8)	(8)	(17)	(18)	(13)	(17)	(20)	(16)
Chhattisgarh	92.27	96.89	80.33	86.25	93.19	89.62	90.38	94.05	90.37
	(7)	(2)	(21)	(14)	(13)	(16)	(12)	(8)	(11)
Goa	98.06	95.24	89.15	93.94		97.21			94.72
	(2)	(5)	(12)	(7)		(2)			(4)
Gujarat	80.17	89.67	90.18	92.76	93.38	94.04	95.49	95.41	91.39
	(19)	(16)	(11)	(9)	(12)	(9)	(4)	(4)	(9)
Haryana	84.04	89.63	96.09	95.63	96.29	96.61	96.38	95.22	93.74
	(15)	(17)	(5)	(4)	(5)	(3)	(3)	(5)	(6)
Himachal Pradesh	89.63	94.90	96.46	94.75	95.93	96.38	95.29	96.43	94.97
	(12)	(7)	(4)	(6)	(6)	(4)	(5)	(3)	(3)
Jammu and Kashmir	68.41		86.79	92.60	94.51	90.68	62.67	66.74	80.34
	(25)		(16)	(10)	(10)	(14)	(25)	(25)	(21)
Jharkhand	81.90	84.26	79.25	78.63	82.67	73.80	72.35	69.61	77.81
	(18)	(21)	(22)	(21)	(21)	(24)	(23)	(24)	(24)
Karnataka	90.62	83.09	82.83	93.66	83.00	87.71	85.19	92.70	87.35
	(11)	(22)	(19)	(8)	(20)	(19)	(13)	(9)	(15)
Kerala	95.09	96.79	98.46	94.84	98.67	97.88	97.75	98.77	97.28
	(5)	(4)	(1)	(5)	(1)	(1)	(1)	(1)	(1)
Madhya Pradesh	98.17	95.21	76.15	76.18	74.64	76.21	75.52	77.29	81.17
	(1)	(6)	(23)	(22)	(24)	(23)	(20)	(19)	(20)
Maharashtra	97.73	98.39	95.77	96.45	94.09	92.83	96.56	97.45	96.16
	(3)	(1)	(6)	(2)	(11)	(12)	(2)	(2)	(2)
Manipur	77.15	92.96	88.52	79.61	97.26	89.93	91.53	82.47	87.43
	(21)	(10)	(14)	(20)	(3)	(15)	(9)	(16)	(14)

Meghalaya	66.15	84.58	68.06	81.84	95.56	95.98	81.34	94.50	83.50
	(26)	(20)	(27)	(16)	(7)	(6)	(16)	(7)	(18)
Mizoram	75.33	86.96	86.70	67.99	83.69	70.98	69.00	86.99	78.45
	(23)	(18)	(17)	(27)	(19)	(27)	(24)	(12)	(22)
Nagaland	71.48	71.25	75.02	75.83	86.34	76.27	90.54	80.08	78.35
	(24)	(24)	(24)	(23)	(16)	(22)	(11)	(18)	(23)
Odisha	92.26	86.66	80.99	85.15	98.52	92.97	85.02	83.82	88.17
	(8)	(19)	(20)	(15)	(2)	(11)	(14)	(15)	(13)
Punjab	92.00	94.11	97.08	96.46	95.48	95.34	95.24	90.36	94.51
	(9)	(9)	(3)	(1)	(8)	(7)	(6)	(10)	(5)
Rajasthan	84.83	96.87	92.22	87.02	90.65	94.28	92.20	85.96	90.50
	(14)	(3)	(9)	(12)	(15)	(8)	(8)	(13)	(10)
Sikkim	55.78	57.04		69.40	75.24	77.11	75.25	73.89	69.10
	(27)	(27)		(26)	(23)	(21)	(21)	(22)	(27)
Tamil Nadu	92.45	90.62	97.23	95.80	96.43	93.00	90.81	84.66	92.62
	(6)	(14)	(2)	(3)	(4)	(10)	(10)	(14)	(8)
Tripura	51.97	64.12	89.06	66.46	70.61	72.43	78.80	89.37	72.85
	(28)	(25)	(13)	(28)	(26)	(25)	(18)	(11)	(26)
Uttar Pradesh	76.91	92.07	87.25	74.68	79.95	80.56	78.43	81.46	81.41
	(22)	(12)	(15)	(24)	(22)	(20)	(19)	(17)	(19)
Uttarakhand	95.75	92.16	92.90	86.76	94.76	96.09	94.15	94.99	93.44
	(4)	(11)	(7)	(13)	(9)	(5)	(7)	(6)	(7)
West Bengal	82.47	91.95	82.94	81.56	86.23	88.88	83.44	74.57	84.00
	(17)	(13)	(18)	(18)	(17)	(18)	(15)	(21)	(17)
Mean	83.30	87.13	86.49	84.55	88.66	86.81	83.98	84.49	85.64

Source: Author's Estimation

Note: Values in the parenthesis are the relative ranks of the States with respect to their Technical Efficiency Scores

Comparison between Elementary Education Expenditure, Outcomes and Technical Efficiency

Table 4 compares the education outcome of the States with the Mean Technical Efficiency Scores. A comparison between Retention Rate and Technical Efficiency Scores tells that Arunachal Pradesh, Mizoram, Nagaland and Jammu and Kashmir have poor access to EE (lower RR) primarily due to inefficiency. However, Rajasthan and Chhattisgarh have low RR despite having an average efficiency of 90 percent. This indicates towards resource scarcity in these States. Bihar, Uttar Pradesh, West Bengal and Jharkhand suffer with the dual problem of resource shortage and technical inefficiency. Kerala, Goa, Haryana and Himachal Pradesh have the highest RR despite having relatively lower public spending.

Meghalaya, Tripura, Assam, Jammu and Kashmir (JK), and Chhattisgarh have the lowest arithmetic scores. Among these States, Meghalaya, Tripura, Assam suffer from both resource scarcity and inefficiency, Chhattisgarh performs poorly primarily due to resource scarcity whereas JK is highly inefficient. Similar conclusions can be drawn if TE scores are compared to reading outcomes. Arunachal Pradesh has the lowest reading score primarily due to inefficiency. While Assam, Meghalaya, and Jharkhand fair poorly because they face a dual problem. Here again JK has low reading score due to inefficiency.

Kerala, Haryana, Himachal Pradesh, Goa, Maharashtra, and Punjab exhibit high efficiency, while their levels of public spending differ significantly. Himachal Pradesh spends ₹58,200 pspa, Haryana ₹44,390, Kerala ₹29,050, Goa ₹24,106, Maharashtra ₹21,563, and Punjab ₹19,365. Despite their efficiency, these States have room for improvement in certain areas. Kerala, Goa, and Maharashtra have the potential to increase public spending to improve arithmetic scores, whereas Punjab faces challenges in improving RR scores. These findings highlight the interdependence of adequate public spending and efficiency in achieving desired outcomes.

CONCLUDING REMARKS

This study measured the technical efficiency (outcome efficiency) of 28 Indian States in providing elementary education. Technical Efficiency has been measured using the Ray Frontier/ Generalized Stochastic Frontier Approach. The output norm (dependent variable) has been estimated using three indicators of elementary education outcome, namely, retention rate at elementary level, arithmetic ability and reading ability. The empirical model has been estimated using the methodology developed in Battesse and Coelli (1995), that simultaneously estimates the elementary education frontier production function and inefficiency model. Any deviation from the frontier indicates that there is scope for the State

Governments to improve the education outcomes without increasing public expenditure (on various inputs).

Table 4: Comparison of Public Expenditure, Outcomes, 2018-19 and Technical Efficiency (Mean)

States	Public Expenditure (per student)	Arithmetic Score	Reading Score	Retention Rate	TE (Mean)
Andhra and Telangana	24435	45.9*	67.7*	75.43	89.72
Arunachal Pradesh	66912	33	47	34.61	67.73
Assam	19097	21.6	48	57.67	74.24
Bihar	11570	46.3	59.8	63.92	86.68
Chhattisgarh	23768	29	72	79.31	90.37
Goa	24106	39.9*	80.2	100	94.72
Gujarat	29449	32.2	68.8	89.52	91.39
Haryana	44390	60.9	79.8	96.47	93.74
Himachal Pradesh	58200	59.7	87.1	96	94.97
Jammu and Kashmir	65033	27.5	52.2	62.86	80.34
Jharkhand	12671	32.7	52.9	56.63	77.81
Karnataka	26361	30.2	56.6	87.36	87.35
Kerala	29050	49.8	85.9	100	97.28
Madhya Pradesh	17070	30.7	58.2	66.11	81.17
Maharashtra	21563	35.9	74.9	94.68	96.16
Manipur	33180	56.5	71.6	52.79	87.43
Meghalaya	22291	10.1	49.8	44.29	83.50
Mizoram	65007	48.9	68.8	46.75	78.45
Nagaland	72396	30.6	55.8	47.2	78.35
Odisha	19153	36.4	68.8	74.33	88.17
Punjab	19365	57.2	80.8	83.1	94.51
Rajasthan	22187	34.1	67.7	65.58	90.50
Sikkim	67974	32.3	62.9	75.25	69.10
Tamil Nadu	34848	43.7	64.7	86.59	92.62
Tripura	7502	20.7	55.1	81.21	72.85
Uttar Pradesh	19776	36	62.2	60.22	81.41
Uttarakhand	47293	41.2	75.4	79.52	93.44
West Bengal	10683	31.1	57.4	59.06	84.00

Source: Public expenditure: estimated based CAG and UDISE data; Arithmetic and Reading Scores: ASER; Retention Rate: UDISE; TE: Author's estimation
* latest data is available for 2014-15

Pertinence of the Ray Frontier model is indicated by the statistical significance of gamma and the coefficients of θ_1 and θ_2. Inefficiency explained 96 percent of inter-state disparity in elementary education outcome. Empirical results show that public spending and better schooling infrastructure improve both access to elementary education (in terms of more retention / less drop-out) and learning outcomes. The inefficiency model shows that there is a scope to increase efficiency in States that have more of SC-ST population. Regular appointment of teachers leads to more efficiency. Rural areas and government schools are less efficient in generating outcomes.

The estimated overall mean technical efficiency of States is 85.6 percent, indicating that about 15 percent of States' potential outputs are not yet realized. There appears to be wide variations (from 67 percent to 97 percent) in the achievement of efficiency among Indian States in generating elementary education outputs.

Kerala, Maharashtra, and Himachal Pradesh are among the most efficient States, whereas Arunachal Pradesh, Sikkim, and Tripura are the least efficient. Lagging States such as Bihar, Jharkhand, Madhya Pradesh, Uttar Pradesh, Assam, West Bengal, and Meghalaya, have a limited scope of improving their outcomes as they suffer from a dual problem of both resource scarcity and inefficiency. Public spending must be increased and the schooling infrastructure must be improved in these States so that they can catch up to the better off States. These findings are similar to that of Mohanty and Bhanumurthy (2020), Dutta (2012) and Sankar (2007). Efficiency has improved in Uttar Pradesh, Gujarat, Haryana, Himachal Pradesh, Meghalaya, and Mizoram over the years, and it has declined in Assam, Bihar, Jharkhand, and Madhya Pradesh. There is a scope for all the States to improve their learning outcomes. States like Goa, Kerala and Tamil Nadu have generated relatively better outcomes with reasonable public expenditure. Policymakers can take inspiration from the best practices in these States while designing public policy for the laggard States.

A key limitation of the study is the exclusion of factors like school environment, socio-demographic barriers, pedagogy, etc., which can impact access and learning. These factors could not be analyzed due to data constraints. Future research can also explore how technical efficiency estimates change due to methodological changes. Despite these limitations, the study results emphasize the necessity for policy interventions to enhance States' performance. The findings may aid policymakers in formulating strategies to address regional imbalances in EE outcomes.

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