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RESEARCH ARTICLE

Global Technical Efficiency and Variable Returns to Scale: Implication on Paddy Production

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Abstract

The paper empirically estimated and decomposed the farm specific global technical efficiency into real technical efficiency and the scale efficiency of the 200 high yielding variety paddy farm households of Jajpur district of Odisha in India by using both Charnes, Cooper, Rhodes and Banker Charnes and Cooper model. The mean global technical efficiency (.849) was explained due to the pure technical efficiency (.890) and scale efficiency (0.94). Out of the 200 sample farms, the number of producing units operating under Constant Returns to Scale, Diminishing Returns to Scale and Increasing Returns to Scale were 35, 31 and 134 respectively. Most of the farms had the potential to increase the technical efficiency. The non-farm variables such as college and high school education of the farm had significant impact in reducing managerial inefficiency in relation to scale inefficiency. The higher the size of the area, the lesser was the managerial efficiency but enhanced scale efficiency. However, the family education and experience of the farm had no significant impact on technical efficiency improvement. Hence, providing education through investment in education and introduction in cooperative farming would increase the global efficiency.

Introduction

Agriculture, the lifeblood of the Indian rural people, has been remained as the key to economic growth in real terms. Of course, the initiatives of Green Revolution in case of food production has mitigated the problem of food crisis, the challenge of food security is still at the forefront of Indian political economy. It is also equally important that in a country like India, where farm production is totally dependent on private investment (76.4% of the total investment in agriculture in 1998-99) – made by the farmers majority of whom are small and marginal- the strategy should be focused on the efficient use of the existing scarce resource (except labour) allocation at farm level under the existing technology. At the same time, the massive increase in population and substantial income growth demands an extra about 2.5 million ton (mt) of food grains annually under the assumption of 3.5 percent growth in per capita gross domestic product. The New Agricultural Policy (NAP) has been drafted to achieve the major objectives of the attainment of 4 per cent annual growth rate in agricultural sector and enhanced level of efficiency of input use consistent with environmental sustainability (Pyakyurial, 2000).On the basis of neo-classical economic theory that a producer is said to be efficient in resource allocation if the optimality conditions are satisfied. Similarly, a producing unit is technically efficient if maximum possible output is obtained from a given quantity of inputs. It is widely observed and empirically proved that substantial variation in technical efficiency, allocative efficiency and economic efficiency among the farms may be due to various factors such as size of farm, use of inputs, access to market information quality components of the farm households (Chennareddy, 1967). The failure of firms to produce at the "best-practicing" frontier which can be called as production inefficiency has been elaborated by researchers (Debreu,1951; Farrell, 1957) on the basis of different approaches. In

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a similar vein, Debreu (1951) and Farrell (1957) proposed that lack of market power on managers in certain cases may cause inefficiencies among the firms. To Leibenstein (1966), the failure of firms to produce on the efficient frontier is by and large motivated by following set of reasons including inadequate motivation, incomplete contracts, asymmetric information, agency problems and attendant monitoring difficulties which are lumped together and form X-inefficiency. Stigler (1976) objected to this approach and put forward that all sources of inefficiency according to Leibenstein can be shown as the evidence for incomplete production model in which whole set of relevant variables are failed to be incorporated (Fried et al: 2008). The pioneering work of Koopmans (1951) provided the earliest formal definition of technical efficiency as: "A producer is technically efficient if, and only if, it is impossible to produce more of any output without producing less of some other output or using more of some input." Subsequently, Debreu (1951) and Farrell (1957) developed a slightly different definition of technical efficiency by ruling out the slack units: "one minus the maximum equi-proportionate (radial) reduction in all inputs that is feasible with given technology and output" (Fried et al: 2008).

The paper used Data Envelopment Analysis approach of Charnes Cooper Rhodes (1978) under the assumption of constant returns to scale and the Banker, Charnes and Cooper (1984) under the variable returns to scale to estimate the farm specific decomposition of technical efficiency scores (Global technical Efficiency) into Pure Technical efficiency and Scale efficiency with different returns to scale. In addition to this the study uses Tobit two-limit regression to measure the impact of non-farm variables such as education of the Farm (in Dummy form) as well as the size of the farm (acres of land) in dummy form. The results suggests that majority of the farms were on the stage of increasing returns to scale and can increase in both technical and scale efficiency. The levels of education (college education has more positive impact on pure technical efficiency than the lower education. The college-educated farms frequently became the peers of others. Farm size has negative impact on both technical and pure technical efficiency but has positive impact on the scale efficiency. Hence better farm education through public investment in education would be appropriate and government should encourage cooperative farming through subsidy of farm techniques to cooperative farms.

Data Envelopment Analysis was first coined by Charnes, Cooper and Rhodes (1978), which had an input-oriented model with constant return to scale (CRS). DEA is a deterministic means of constructing piece-wise linear approximation to the smooth curve based on the available sample. The distribution of sample points is observed and kinked line is constructed around the outside of them 'enveloping' them (hence called Data Envelopment Analysis (Charnes, Cooper and Rhodes , 1978). This method, which is currently known as basic DEA, was an extension of "Farrell's measure to multiple-input multiple-output situations and operationalized it using mathematical programming". A slight extension of DEA model is the decomposition of technical efficiency score into components resulting from the scale operations, surplus inputs which can not be disposed of and pure technical efficiency In subsequent researches, Banker, Charnes and Cooper (1984), variable returns to scale (VRS) models were developed and introduced to the DEA literature. The VRS model allows the best practice level of output to inputs to vary with the size of Decision Making Units (DMU). The VRS frontier passes through the points where the DMUs have the highest input to output ratio over their relative size. The scale efficiency scores of each DMU can be determined by comparing the technical efficiency scores under CRS and VRS. The distance from CRS and VRS frontier determines TE under CRS and VRS. The distance between the CRS and VRS determines the scale efficiency components. The technical efficiency resulting from factors other than scale is determined by the distance from VRS, the efficiency scores for each DMU indicate only technical inefficiency resulting from non-scale factor. Hence, VRS scores will be higher than or equal to those obtained under CRS. Comprehensive reviews of the DEA and stochastic frontier approaches are provided by Kalirajan and Shand (1999); Charnes et al. (1994); Coelli (1995); Lovell (1993); Green (1993); Ali and Seiford (1993); Fried et al. (1993); Bravo-Ureta and Pinheiro (1993); Bjurek et al. (1990) and Bauer (1990). Given the alternative empirical tools available, the choice as to the 'best' method is unclear (Olesen et al. 1996). Few rigorous empirical analyses have been carried out in assessing the sensitivity of efficiency measures to the choice of DEA and parametric methodology in agriculture (e.g., Sharma et al.1999; Wadud and White 2000). The limited findings show that efficiency score estimates from each approach differ quantitatively, although the ordinal efficiency ranking of farms obtained from the two approaches appear to be quite similar. The evidence would suggest that the choice is somewhat arbitrary, though to a certain degree the choice between alternative modeling approaches depends upon the objectives of the research, the type of farms and assumptions regarding the data generating process.

Materials and Methods

In Farrell's (1957) concept, the overall efficiency (OE) is a multiplicative combination of Technical Efficiency (TE) and Allocative Efficiency (AE), so that OE = TE * AE. Technical Efficiency is the conversion of the physical inputs (land, labour, fertilizer, irrigation) into output relative to the best practice. Given the current technology, there is no wastage of inputs whatsoever in producing the given quantity of outputs. A DMU at best practice is said to be 100 per cent technically efficient. If operating below best practice levels then the DMU's technical efficiency is expressed as percentage of the best practiced virtual DMU. Managerial practices and the scale or size of operations affect technical efficiency, which is based on engineering relationship but not on prices and cost.

Allocative Efficiency (AE) refers to whether inputs, for a given level of output and set of input prices are chosen to minimize the cost of production assuming that the DMU being examined is already fully technically efficient. AE also expressed as percentage score, with a score of 100 percent indicating that the DMU is using its inputs in proportion, which would minimize cost. A DMU that is operating at best engineering best practice could still be allocatively inefficient because of not using the inputs in the proportion, which minimizes its cost. Finally cost Efficiency or Economic Efficiency (EE) refers to the combination of TE and AE. It is calculated as the product of TE and AE.

Data Envelopment Analysis (DEA)

One of the mainstream methods of efficiency analysis is DEA, which doesn't presume any functional form for production. It basically "involves the use of linear programming methods to construct a non-parametric piece-wise surface (or frontier) over the data" (Coelli et al, 2005). Therefore, efficiency of each DMU , which can be a bank, hospital, university, agricultural farm and so forth is calculated regarding to the "best practising" producer.

The common feature of estimation techniques based on Farrell's (1957) efficiency definition is that the information is extracted from extreme observation in the sense of technical efficiency to form the best practice production frontier. This makes DEA scores sensitive to error in data. However, the main advantage of DEA approach is that it does not require the assumption of functional form for the specification of input output relation. Technical efficiency in terms of optimal combination of inputs to achieve a given level of output (input orientation) is more appropriate

Methods of Analysis

Under the Charnes, Cooper and Rhodes (1978) model better known as CCR model the ratio of the sum of output weight to the the sum of input weight for a particular DMU is maximized. Given the n DMUs, DMU_1, DMU_2,.........,DMU_n (on the assumption that numerical data are available for these j = 1,........, n DMUs and the DMU prefer more output and lee input), m input items and s output items, the input output data for DMU_j be x_{1j}, x_{2j},........x_{mj} and (y_{1j}, y_{2j},........,y_{sj}) respectively. The input data matrix X and output data matrix has (m x n) and (s x n) dimensions respectively. Given the data the efficiency of each DMU is measured once and hence for n DMUs n optimizations are needed. The Fractional Programming for DMU_0 is solved to obtain the values of input weight (υ_i) (i = 1,2,......,m) and the output weight (u_r) (r = 1,2,........s) as variable

$$(FP_0)\quad \max_{(\upsilon,\, u)} \quad \theta = \frac{u_1y_{10}+u_2y_{20}+,........,+u_sy_{s0}}{\upsilon_1x_{10}+\upsilon_1x_{10},.......,+\upsilon_1x_{10}} \quad ....4.1$$

subject to

$$\frac{u_1y_{1j}+u_2y_{2j}+,........,+u_sy_{sj}}{\upsilon_1x_{1j}+\upsilon_1x_{2j},.......,+\upsilon_1x_{mj}} \leq 1 \quad (j=1,..,n).......4.2$$

$$u_1, u_2,....u_s \geq 0 \text{ ....4.3}$$

$$\upsilon_1, \upsilon_2,....., \upsilon_m \geq 0 \text{ ....4.4}$$

The equation 4.2 implies that the ratio of virtual output to virtual input should not exceed 1 for every DMU. The nonnegative constraints for the weight imply that all the outputs and inputs have nonzero worth. The (FP_0) can be replaced by the LP_0 as follows.

(LP_0) $\max\limits_{\mu, \upsilon}$ $\theta = \mu_1 y_{10} + \mu_2 y_{20} +, \ldots, + \mu_s y_{s0}$..4.5

Subject to $\upsilon_1 x_{10} + \upsilon_2 x_{20} +, \ldots, + \upsilon_m x_{m0} = 1$..4.6

$\mu_1 y_{1j} + \mu_2 y_{2j} +, \ldots, + \mu_s y_{sj} \leq \upsilon_1 x_{1j} + \upsilon_2 x_{2j}, \ldots, + \upsilon_m x_{mj}$..............4.7

$\upsilon_1, \upsilon_2, \ldots, \upsilon_m \geq 0$..4.8

$\mu_1, \mu_2, \ldots, \mu_s \geq 0$..4.9

The optimal values of (LP_0) be $(\upsilon = \upsilon^*, \mu = \mu^*)$ and the optimal objective value $\theta = \theta^*$. The optimal values obtained through (FP_0) and (LP_0) are independent of the units in which inputs and outputs are measured provided these units are same for every DMU (Cooper et.al, 2005). The DMU is CCR efficient if $\theta^*=1$ and there exists at least one optimal value (υ^*, u^*) with $\upsilon^*>0$ and $u^*>0$, otherwise DMU_0 is inefficient.

The Vector matrix notation of the (LP_0) in 4.5-4.9 in multiplier form can be expressed as

$\max\limits_{\upsilon, u}$ uy_0 ------------4.10

Subject to $\upsilon x_0 = 1$............4.11

$\upsilon X + uY \leq 0$..........4.12

$\upsilon \geq 0, u \geq 0$.............. 4.13

The dual to the LP_o (4.10-4.13) with real variable θ and transpose T of a nonnegative vector $\lambda\ (\lambda_1, \lambda_2, \lambda_3 \ldots\ldots \lambda n)^T$ of a variable as follows

(DLP_0) $\min\limits_{\lambda, \theta}$ θ 4.14

Subject to $\theta x_0 - X\lambda \geq 0$.............4.15

$Y\lambda \geq y_0$..................4.16

$\lambda \geq 0$.........................4.17

The DLP_0 (4.14- 4.17) has feasible solution $\theta^* = 1, \lambda_0 = 1, \lambda j = 0\ (j \neq 0)$. The value of $0 < \theta^* \leq 1$. Whenever $\theta^* < 1$, $(X\lambda, Y\lambda)$ outperforms $(\theta x_0, y_0)$. Hence, the output excess $s^{-*} \in R^m$ and the output shortfalls $s^{+*} \in R^s$ as

$s^- = \theta x_0 - X\lambda$ and

$s^+ = Y\lambda - y_0$

To discover the possible input excess and output shortfall the LP problem is solved for the optimal value θ^* - called Farrell Efficiency. The value of θ^* is incorporated in the II phase of DLP_0 (Cooper et.al. 2005). If the optimal solution $(\theta^*, \lambda^*, s^{-*}, s^{+*})$ of the two phase programme satisfies (i) $\theta^*=1$ and (ii) is zero slack $(s^{-*}=0, s^{+*}=0)$ then the DMU is called CCR efficient, otherwise not. The first of the two conditions referred to technical Efficiency and the slack variables represent mix inefficiency. The condition (i) and (ii) taken together is called "Pareto Koopman" or "strong" efficiency.

The extension of CCR model made by Banker, Charnes Cooper (1984) (BCC) is characterized by the production frontier spanned by the convex hull of existing DMUs and the frontiers have piece-wise linear and concave characteristics with Increasing Returns to Scale (IRS), Decreasing Returns to scale (DRS) and Constant Returns to Scale (RTS). The input oriented BCC model evaluating the efficiency of DMU_0 by solving the envelop form of linear programming.

(BCC_0) Min θ_B **4.18**

θ_B, λ

Subject to $\theta_B x_0 - X\lambda \geq 0$............**4.19**

$Y\lambda \geq y_0$..................**4.20**

$e\lambda = 1$ **4.21**

$\lambda \geq 0$........................**4.22**

Where θ_B is a scalar. The primal BCC_0 is solved using a two-phase procedure. In the first phase θ_B is minimized and in the second phase the sum of input excess and output shortfall is maximized keeping $\theta_B = \theta_B^*$. In an optimal solution ($\theta_B^*, \lambda^*, s^{-*}, s^{+*}$) obtained in the two-phase process for (BCC_0) satisfies $\theta_B^* = 1$ **and has no slack** ($s^{-*} = 0$, $s^{+*} = 0$) then the DMU is called BCC efficient, otherwise not. For a BCC-inefficient DMU_0 the reference set E_0, based on the optimal solution λ^* by

$E0 = \{ j \mid \lambda_j^* > 0\}$ ($j \in \{1.......n\}$)

The sources of inefficiency of a DMU may be from two sources. It may be caused by the inefficient operation of the DMU itself or by the disadvantages conditions under which the DMU is operating. CCR model assumes CRS that is their radial expansion or reduction of all observed DMU and their non-negative combinations are possible and CCR scores are called Global Technical Efficiency. On the other hand, BCC model assumes convex combinations of observed DMUs from the production possibility set and the BCC scores are called Pure Technical Efficiency. If the DMU is full efficient under CCR and BCC then it is operating in the Most Productive Scale Size (MPSS). If the DMU is fully efficient in BCC but inefficient in CCR, then it is operating locally efficiently but not globally efficiently due to scale size of the DMU. The Scale efficiency is defined as

SS= (CCR Efficiency/BCC Efficiency)

Type, Source of Data

The primary data on the 200 farm households about the Paddy production has been and collected from the **Korei** block of Jajpur district Odisha, India. Out of seven revenue villages five of the **Goleipur** Panchayats have been surveyed. The farm households under the considerations have been surveyed personally with the help of ready-made questionnaire, which was framed both in English and Oriya script to enhance the understanding and self-study of the farm households. The area of study is chosen because of their geographical location i.e., the area is well connected to the national Highway 5 that connects Calcutta to Chennai. The area is also connected to the big markets such as Jajpur Road, Panikoili, Kuakhia and Chandikhole and the state head quarter Jajpur. The output is expressed in Indian Rupee ('), the Value of capital is expressed as (12%) of the total value of all the fixed assets (cow shed, granary, storage house, others). The other inputs are Land under the crop (in acres) Labour days, Bullock Labour days, Fertilizers in (kgs), manures (in quintals), pesticides (grams) and Tractor Hours. The Education of the Effective Head is also used as a categorical variable (College Education, High School and Primary education). Again Land area is also used as a categorical variable (small and large farm size)

Analysis of Results.

The summary of the inputs and out of the sample effective farm household farm households was presented in the Table-1.

Table-1: Basic Statistics on the inputs and Output used by the DMUs

Items	Minimum	Maximum	Average	Standard Deviation
Paddy Output (`)	13800	70560	33436	10812
Capital expenditure (`)	2300	6800	4816.25	730.632
Land (in Acres)	2	8	4	1
Labour (Man days)	192	832	408	125
Bullock Labour (days)	12	80	36	13
Manures (quintals)	168	2120	885	302
Fertiliser (kgs)	100	7500	1023	596
Pesticides (grams)	60	1200	188	98.9
Tractor (in Hours)	2	28	9	5
Education (School)[1]	3	15	8	2
FamEdu(yearSchool)	3	19	8	3
Exp (years)	8	20	12	3

[1] The education is of the effective head of the household i.e. the individual who is the actual cultivator and may or may not be the head of the house. The FamEdu is the average education of the family as a whole.

The information suggested that the average land is 4 acres with maximum of 8 acres and minimum of 2 acres. That means average farm households are small farmers. The maximum value of output was ` 70,560 with minimum of `13800. The average education of the effective Head was 8 years with maximum 15 years and minimum of 3 years.

The technical efficiency (Global technical efficiency) under the CCR model and the efficiency scores under the BCC model have been estimated by using the DEAP software (Coelli, 1996). The frequency distribution of efficiency scores (θ^*) under CCR (equation 4.14 to 4.17) and BCC model (equation 4.18 - 4.22) is presented in the Table-2.

As per the results obtained from using the DEA software (Coelli,1996), the mean CCR technical Efficiency (here after CCR-TE) was 0.849. 33 per cent of the 200 DMUs were lying within the range of 90% and above level of CCR-TE.. 30 per cent of the total were within the range of 80 to less than 90 per cent range. 32 per cent of the total sample DMU had achieved the scores between 70% and less than 80%. The total number of DMUs having 70% and above scores (CCR-TE) was 190 exactly 95% of the total sample. The number of DMUs below the mean CCR-TE is 106 the minimum score 0.649 with a standard deviation of 0.102

As far as the BCC Technical efficiency Score (here after BCC-TE), the mean is 0.890 with a standard deviation of 0.09. The total number of DMUs having scores more than and equal to 70% was almost 100%. The minimum score was .691 and the number of DMUs below the mean BCC-TE is 99 that was almost 50% of the total farms. The number of DMUs achieving full efficiency under CCR and BCC model is 35. That means 35 DMUs are most productive in Scale Size (MPSS) (when the efficiency score under CCR and BCC model became one and hence scale efficiency was also one) as in Cooper et.al (2005). Among all the MPSS DMUs the165th DMU is the most referred DMU (with peer count 119 times).

A total of 35 DMUs were operating under the CRS (the scale efficiency equals one) (Table-3). Thirty One DMUs were operating under the DRS and a total of 131 DMUs were operating under IRS. Among the CRS DMUs the 165th DMUs had highest number of peer counts (119) followed by 186th DMU (74) and 11th DMU (68). These DMUs have been acted as reference producer for many of the sample farms under the study. The economic implication is that these farms could be radially expanded without alternating the input ratio. Except eight DMUs operating under CRS, all other DMUs (27) have zero slacks in input use. It means they used the inputs most efficiently with optimal managerial and scale efficiency. The rest 8 DMUs had not achieved full global technical efficiency because of pure managerial inefficiency and not due to scale inefficiency. Hence, efficient management of the input use can radially reduce the excess input use to achieve a given level of output. Among the input excesses, the maximum possible reduction can be made in case of fertilizer and manures. Most often the farm households used excess of fertilizer and manures in the believe that it can increase the output. As far as the reference DMUs for these DMUs were concerned, more weight was assigned to DMUs who had higher level of education in forming the virtual DMU.

Table- 4 reported the peers and the weights forming a virtual DMU for a particular DMU under the CSR experiencing only pure technical inefficiency. Except the weight of 165th DMU, which had been counted as the most referred DMU for others, the DMUs having higher schooling had received more weight. For Example, 31st DMU had given 32.4 % weight to the 11th DMU in forming virtual DMU. Similarly, 8th DMU receives 62.6% weight for 35th's virtual DMU.If the DMUs wre examined on the basis of their levels of formal schooling completed, out of 34 college educated DMUs (11-15 years of schooling completed), three DMUs performed below the mean CCR-TE. The best performers among these college educated DMUs are 7th,8th, 11th, 13th, 17th,22nd,

24^{th}, 25^{th}, 26^{th} and 27^{th} . However, 11^{th} DMU was the best performer among them with maximum times becoming the peer DMU (68 times) for others followed by 3^{rd}, (51 times) and 7^{th} DMU (38 times). Out of 87 high school (8-10 years of schooling) educated DMUs, 47 DMUs performed below the mean CCR-TE. In this category, $13^{th,}$ 46^{th} and 118^{th} DMU are 100% CCR and BCC efficient, hence were achieving MPSS. The most referred DMU in the group was 46 (60 times) followed by 118^{th} DMU (52 times). Out of the 79 primary school educated DMU, 57 DMUs were performing below the men CCR-TE. Among them 8 DMUs were performing under MPSS. It is also interesting that 165^{th} DMU is the highest number of times referred by other DMUs (from 200 DMUs).

Table-2: Frequency Distributions for Efficiency Scores under CCR and BCC Model

Class Interval (Efficiency (θ*)	(θ*) CCR Model	(θ*) BCC Model	(θ*) Scale Efficiency
0.5-0.6	0	0	0
0.6-0.7	10 (5)	1 (.5)	1(0.5)
0.7-0.8	64(32)	37(18.5)	7(3.5)
0.8-0.9	60(30)	67(33.5)	25(12.5)
0.9- upto 1.0	66(33)	95(47.5)	167(83.5)
Mean ((θ*)	0.849	0.890	.954
S.D	0.102	0.09	0.062
Min Value	0.641	0.691	0.676

Table-3: DMUs under CRS

DMU	Peer Frequency	DMU	Peer Frequency	DMU	Peer Frequency	DMU	Peer Frequency
1	21	25	27	100	2	160	2
3	51	26	4	102	5	165	119
7	38	27	17	106	5	166	38
8	16	43	3	109	2	167	2
11	68	46	60	118	52	181	23
13	1	56	10	121	6	183	2
17	2	74	1	128	37	186	74
22	2	93	4	140	1	188	13
24	7	96	18	146	2		

Table-4: Peers and their Weights for DMUs under CSR

DMU	Peer DMU (λ)*	Peer DMU (λ)	Peer DMU (λ)	Peer DMU (λ)	Peer DMU (λ)	Peer DMU (λ)
5	7(100)	-	-	-	-	-
29	165(.486)	46(.215)	7(.108)	181(.043)	11(.147)	-
31	165(.318)	121(.100)	11(.324)	188(.183)	13(.075)	-
33	128(.001)	27(.446)	118(.076)	166(.038)	7(.092)	165(.347)
35	166(.004)	181(.015)	7(.034)	93 (.083)	165(.237)	8(.626)
66	106(.177)	181.066)	7(.388)	165(.028)	11(.129)	46(.212)
99	43(.032)	3(.017)	128(.113)	165(.715)	7(.122)	-
168	118(.022)	128(.004)	27(.314)	116(.037)	7 (.089)	165(.534)

*** Values are the weights of the DMU in forming a virtual DMU.**

On the other hand, the BCC efficiency scores provided evaluations using a local measure of scale-Variable Returns to Scale (VRS). Under this model, 16 DMUs accorded fully BCC-TE (score is 1) in addition to those 35 100% CCR-TE DMUs, which retain their previous efficient status.

The full efficiency with the BCC model was caused by the use of its smallest amount of inputs even though it was lowest in the CCR score (Theorem 4.3)

(Cooper et. al. 2005). For example 52nd DMU had the highest value of output (70560). Out of 34 college educated DMUs, six performed below the mean BCC-TE and 12 DMUs are MPSS. Among 87 high school educated DMUs 42 DMUs had scores below the mean BCC-TE. Among the 79 primary educated DMUs 50 DMUs performed below the mean BCC-TE. That mean around 63% of the primary educated DMUs perform below the mean score and it was only 48% in case of high school educated DMUs. Hence, there was differences in managerial efficiency with respect to the levels of schooling.
In case of Scale Efficiency (SE) (CCR-TE / BCC-TE), except two DMUs all 33 college educated DMUs were above the mean SE. In case of the second category, 19 DMUs are below the mean SE and it was 44 for the primary educated DMUs. Hence, the CCR-TE of high school educated DMUs were mainly due to BCC-TE that was due to managerial efficiency, which could be radially reduced without changing the scale of the operation. However, for the primary educated DMUs the CCR-TE was due to both managerial and scale inefficiency hence they were mixed inefficient.

As far as the return to scale was concerned, almost 170 DMUs were operating under the IRS. It implies that except 30 DMUs all other DMUs had prospective to increase the efficiency. It should be noted that the individual DMU did not perform under 100% CCR-TE as well as BCC-TE whenever the farm size exceeded a particular limit (2 acres). It became difficult to manage a DMU with bigger land size (more than 2 acres) because; managerial skill is an indivisible factor that cannot be increased proportionately in comparison to the other inputs. A bigger farm size DMU was associated with large amount of fixed assets for which, extra amount of labour power is hired for its proper management. Hence, the individual DMU could pool their resources for cooperative farming, which not only would reduce wastage of input use but also would reduce the managerial inefficiency due to increase in the number of the DMUs. The study made by Toluwase and Apta (2013) concludes that farmer cooperative is an important tool for increasing productivity. Ariyaratne et.al (2006) found that agricultural cooperatives encourages technological improvement and helps efficiency improvement.

The analysis of the results input slacks (s-*) of these DRS DMUs indicated that most of them had large land area under cultivation (average of 5- 6 acres) with a maximum size of 8 acres of land. Out of all 31 DMUs, except two DMU, had 5 to 8 acres of land. It means higher farm size had achieved their capacity and output is increasing at a diminishing rate. The higher farm size DMU, hence, achieve low efficiency owing to mix inefficiency. Due to large land size, the DMUs excess amount of fertilizer and manures, resulting inefficiency. The impact of education with different category (College education$11\leq D1\leq 15$; $8\leq D2\leq 10$; $3\leq D3\leq 7$) and land as a dummy variable for large size and small size (≤ 2 acres;>2 large farmers)

In the first stage of the analysis, the technical efficiency of individual farms is evaluated by the DEA. Since the production frontier in the DEA approach is deterministic, the resulting efficiencies contain noise from data. Therefore, in the second stage of this analysis, the features of the operating environment (farm characteristics) are used to explain the computed technical efficiency scores by estimating an efficiency model. As it follows from the DEA efficiency score definition, the DEA score falls between the 0 and 1, making the dependent variable (efficiency score from the first stage of analysis) a limited dependent variable. Therefore, the Tobit model is suggested (e.g., Cooper 1999; Grigorian and Manole 2002) as an appropriate model in the second stage of analysis when considering the effects of a farm's characteristics on the farm's efficiency score.
In order to know the impact of the social variable on the different categories of Efficiencies (CCR –TE, BCC-TE and SE) Two-Limit Tobit regression had been used to estimate the coefficients and to know the marginal effects of categorical variable on CCR, BCC and Scale efficiency. The models for CCR-TE, BCC-TE, and SE in equation - 4.23 were estimated separately using the two-limit Tobit procedure, given that the efficiency indices are bounded between 0 and 100 per cent (Greene 1991; Hossain 1988).

EFFIC = f(fam Edu, Exp, edu dummy , Land Dummy)........................4.23
Education Dummy of the DMU is D_1 (for college Education (11-15) =1 otherwise 0; for high scool Education 8-10 is 1 otherwise 0 and the base is primary education 3-7). For land dummy (D_3) if area is greater than 2 acres D_3=1 otherwise 0). Table-5 shows the parameters of Tobit regression.

Table-5 :Two-Limit Tobit Equation for CCR, BCC and Scale Efficiency

variables	CCR-TE Parameter (t-values)	BCC-TE Parameter (t-values)	Scale-Efficiency Parameter (t-values)
constant	0.85481(17.83)**	0.9648(25.73)**	0.87325(28.37)**
Fam-Edu	-0.001562(0.47)	-.000629(0.24)	-0.00162(.75)
Exp	.001689(0.62)	.00108((.51)	0.00085(.49)
D_1	0.17712 (7.11)**	0.09890(5.10)**	0.08950(5.43)**
D_2	0.07550 (4.56)**	0.036104(2.74)*	0.04775(4.45)**
D_3	-0.0740313(2.61)*	-0.12330(5.76)**	0.05938(3.35)**
Log Likelihood	128.7882	228.6542	191.25

As far as the parameters were concerned the D_1 and D_2 have significant impact on the improvement of CCR-TE , BCC-TE and Scale Efficiency (Braveo et.al, 1993). However, there was negative and significant relationship between size and efficiency (CCR-TE and BCC-TE). It means the smaller farms manage the production process in an efficient manner. But in case of scale efficiency is positive implying that the scale efficiency improves with higher farm size. It is noteworthy that Rudra (1968) concludes that "there is no scope for propounding a general law regarding farm size and productivity relationship". Chattopadhyay and Sengupta (1997) in the context of West Bengal, report that the inverse relation between farm size and productivity was stronger in agriculturally developed regions. On the other hand, Hanumantha Rao (1975) and Subbarao (1982) report a positive relationship between farm size and productivity and attributed this to higher application of fertilizer and other cash-intensive inputs on large farms. Dyer (1997) argues that the inverse relationship is neither a product of superior efficiency on the part of small farms nor is it due to better quality land on the small farms but arises from the desperate struggle for poor peasants for survival on below subsistence plots of land.

The marginal Effects of the Dummy variables on the three efficiency score were presented in the Table-6. It indicated that increase in the school education from high school to college level increased the efficiency (CCR-TE) by 9.8 per cent and from primary to high school CCR-TE increases by 3.6 per cent and in case of BCC-TE, it was 17.71% and 7.5% respectively. As far as Scale Efficiency was concerned, the corresponding values are 8.9% and 4.7% It means the impact of the lower education increasing the efficiency was less. The complementarities of education with the access to new information, decoding the relevant information, the use of new inputs, adoption of new methods of production and reaping the maximum benefit out of it makes it very much useful to for the more educated farmers, in addition to other primary inputs, on improving individual farm efficiency. Hence, higher education has more contribution in reducing managerial inefficiency rather than reducing scale inefficiency. Ever since Chaudhuri (1974) has articulated this idea as *"Lapses back into illiteracy"*. According to *Nelson-Phelps-Schultz hypothesis* (1986) the effect of education is supposed to differ over time, as time passes and new technological diffusions are made in the field of agriculture, the knowledge from either primary schooling or from higher primary schooling will be totally useless in acquiring useful information and decoding them for the farm practices. In case of area (D_3) there was negative impact of higher area under cultivation on pure technical efficiency but there was positive impact of about 5.9% of increasing the area under cultivation from 2 acres to three acres and above. Hence, rather increasing area of individual DMU if the DMUs could bring together there resources and go for cooperative farming, the scale efficiency will improve (Toluwase and Apta 2013; Ariyaratne et.al 2006).

Table-8: Marginal Effects of Dummy Variable on Efficiency Score

Variable	CCR-TE dy/dx(Z-value)	BCC-TE dy/dx(Z-value)	SE dy/dx(Z-value)
FamEdu	-0.00629(.24)	-.00156(0.47)	-0.00162(0.75)
Exp	.001083(.51)	0.00168(.62)	0.000858(0.49)
D1@	0.098(5.10)**	0.17712(7.11)	0.0895(5.43)
D2@	.0361(2.74)*	0.07550(4.56)	0.04775(4.45)
D3@	–0.123(5.76)**	-0.074(2.61)	0.0593(3.35)

@- dy/dx is for discrete change of dummy variable from 0 to 1.

Conclusion

The Global Technical Efficiency (CCR-TE) is a product of Pure Technical Efficiency (BCC-TE) and Scale Efficiency (SE). In case of the CCR-TE, 106 DMUs are performing below the mean CCR-TE (0.849). Thirty Five DMUs are achieving MPSS. The CCR-TE scores for the college educated DMU are better than the high school and primary school educated DMUs. The number of Peer counts is more for the DMUs with higher levels of Education. Under the BCC model, 99 DMUs are performing below the mean BCC-TE (0.890). In addition to those 35 DMUs, 16 more DMUs have accorded !00% BCC-TE even though they are not 100% CCR-TE. The

BCC-TE scores are also differentiated with respect to levels of Education. The mean technical efficiency of the DMUs is explained due to the product 89% pure technical efficiency and 95% of Scale efficiency. As far the impact of non-farm (social) variables are concerned, comparatively college education has more contribution to managerial efficiency than the scale efficiency. Bigger size of land reduces both Global technical and pure Technical efficiency but increases scale efficiency. Hence, the policy should be aimed at investing more on schooling and education in the rural areas especially to the farmers. Better extension facilities and training programme such farm tour to different places specifically agriculturally advanced regions should be given priority. Secondly, emphasis on better cooperative farming (pooling of individuals farm resources together) can yield better result than concentrating on the large farms, which lack higher managerial efficiency. The education system must be farm reoriented to serve the needs of the rural community in boosting agricultural production and productivity to meet the future rising food demand and reducing hunger and malnutrition from the society.

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