Title:

Evaluating Interventions in Developing Country Agriculture: The Productive Efficiency and Related Analytical Issues

Short Title: **Evaluating Interventions with Productive Efficiency**

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Abstract

Productive efficiency, a widely used estimate for evaluating interventions in agriculture, is sensitive to specifications of econometric models and analytical approaches. These methodological issues likely to vary from one production environment to another. Hence it is important to select an appropriate combination of the specifications of the econometric model and analytical approaches in order to get unbiased and efficient estimates. This study, however, looks into some of the crucial specifications of the stochastic frontier model and analytical approaches that apply to developing country agriculture. The empirical evaluation of two competing interventions, namely, the Silt-dredging and Regulated-drainage Management (SRM) and the Tidal River-basin Management (TRM), estimates stochastic frontier model for rice production with different specifications, (e.g., normal half-normal, normal truncated-normal, error component etc.) involving alternative analytical approaches (e.g., pooled modeling vs. individual modeling etc.). The mean productive efficiency (technical) scores obtained from the pooled model are 0.769 and 0.707 respectively for the SRM and the TRM, whereas these scores from the individual models are 0.854 and 0.976 in order. However, both of the model diagnostics (e.g., σ^2 and γ) are found statistically highly significant with the pooled model, unlike the individual models. Meanwhile, a translog functional form of the frontier pooled model came up with biased estimates, unlike the Cobb-Douglas form. In fact, the pooled model with normal truncated-normal distributional having Cobb-Douglas functional form came up with consistent and statistically significant outcomes.

Keywords: Stochastic production frontier, technical efficiency,

Introduction

Different types of interventions/development strategies are taken up in agriculture for a variety of purposes including protection of agricultural land and the environment (CEGIS, 2007; ADB, 2007; Rouf, 2015), intensive use of land (Eknayeke and Jayasuria, 1987; Kalirajan and Shand, 1986), enhancement of farm output (Tadesse and Krishnamoorthy, 1997; Dawson et al., 1991; Dawson and Lingard, 1991), and so on. However, evaluation of these interventions in terms of their performance is very important because of large economic and environmental impacts involved. In agriculture, evaluation of interventions should consider the extent of their contribution to output growth which is reflected through productive efficiency. Usage of productive efficiency of the production units associated with the interventions is an established practice both in agriculture and industry (Bravo-Ureta et al., 2007, Coelli et al., 2005; Thiam et al., 2001). However, productive efficiency can be estimated in a number of alternative ways in terms of the specification of the econometric model and analytical approaches. Hence, the main challenge relates to the selection of an appropriate methodological package since productive efficiency is very sensitive to model specifications and analytical techniques.

Stochastic frontier model is commonly used to estimate productive efficiency in agriculture. However, construction of the model as well as its estimation can be carried out in several alternative ways depending on the circumstances. For example, a stochastic frontier model can assume a variety of features in terms of distribution of the error terms, presence of inefficiency effects, functional form of the model and so on; while analytical approach can accommodate different types of approaches including pooling the data. So, it is important to employ the right form of the frontier model and analytical approach to have unbiased and efficient estimates. This study, however, focuses primarily on some of the crucial aspects of the stochastic frontier models and analytical approaches that apply to developing country agriculture and then examines them with an empirical study.

Selection of a frontier model with right specifications and then its estimation are influenced by a number of factors associated with the production system, way of farm management as well behaviour of the farm operators etc. And these factors differ more or less between developing country agriculture and developed country agriculture. For example, in the developing countries farmers often skips one or more of the input items in growing their crops (Battese, 1997) either due to financial hardship, or unavailability of a particular input or because of a perception that it would make little difference in the level of output etc. According to Battese (1997, p. 250), 'if the number of ‘zero cases’ is a significant proportion of the total number of sample observations, then the procedure may result in seriously biased estimators of the parameters of the production function'. Hence, functional form to be chosen with care. On the other hand, developing country agriculture is dominated by subsistent farming unlike the developed country agriculture, so farming practice as well as farm management considerably differ between them. As a result, stochastic production frontiers for the same crop likely to appear with varying degrees of compliance with the Zellner et al., (1966) argument of expected profit maximisation. Thus the methodological package for estimating productive efficiency may not be the same for developing country agriculture and its counterpart. This paper, however, looks into some of the distinguishing aspects of developing country agriculture that need to be considered while estimating productive efficiency with stochastic frontier analysis. Two competing interventions —the Silt-dredging and Regulated-drainage Management (SRM) and the Tidal River-basin Management (TRM)—implemented in two depressed areas in the Southwest coastal zone of Bangladesh to boost agricultural productivity through improving the production environment are taken as a case study. The SRM is characterised as a hard engineering structural approach; in contrast, the TRM is known as a non-structural natural approach. Meanwhile, the debate over the appropriateness of these two types of intervention motivated us to carry out this study.

Theoretical Framework

Productive efficiency and stochastic frontier model

It is well known that any major intervention in agriculture affects the production environment and/or production process of the produce(s) involved, whereby resource usage patterns, employment opportunities, cost of production, total output and so on take new shapes and sizes. So, performance evaluation of an intervention in terms of its contribution to be assessed by the productivity of the production units involved. The logic here is that the input-output relationship of a production unit or a farm is mostly determined by the associated production environment/production process which is brought forth by the intervention itself. Thus, the productive efficiency of a production unit is eventually be attributed to the intervention implemented to exploit the production units. This is a well-recognised approach by which a wide variety of interventions are assessed in terms of productive efficiency (see Eknayake and Jayasuria, 1987; Coelli et al., 2005, p. 1; Coelli and Battese, 1996; Kalirajan 1981,1982 and 1984; Kumbhakar et al., 1989; Von Baily et al., 1989; Rouf, 2015). There are three forms of productive efficiency, e.g., technical efficiency, allocative efficiency and cost efficiency. However, technical and cost efficiencies apply to performance evaluation of an intervention (see Kalirajan and Shand, 1986; Seyoum et al., 1998; Speelman et al., 2008), since allocative efficiency mostly relates to the performance of the operators/managers of the production units. Førsund et al., (1980) report that it is appropriate to employ either a production frontier (for technical efficiency) or a cost frontier (for cost efficiency) in evaluating the performance of an intervention. Meanwhile, Kalirajan and Shand (1999) put more emphasis on production frontier. In fact, the usage of technical efficiency has overwhelmingly outnumbered that of other productive efficiencies in the literature of performance evaluation (see Battese, 1992; Thiam et al., 2001; Coelli, 1995; Bravo-Ureta et al., 2007). It is worth mentioning here that when output is stochastic and endogenous, the farming practice complies with the Zellner et al., (1966) assumption of mathematical expectation of profit maximisation, hence technical efficiency is the appropriate productive efficiency to evaluate an intervention (see, Kumbhakar and Lovell, 2000, p.132)

However, the typical form of a stochastic production frontier model (Aigner et al., 1977) is given by

$$y_i = f(\boldsymbol{x}_i ; \boldsymbol{\beta}).\exp \varepsilon_i ; \quad \varepsilon_i = \xi_i - \tau_i \text{ and } -\infty \leq \xi_i \leq \infty; \tau_i \geq 0 \quad (1)$$

where, y_i is the output of the i-th production unit, $(i=1, 2, 3, \ldots n)$; $x_i = (x_{1i}, x_{2i}, \ldots x_{mi}) \geq 0$; $\boldsymbol{\beta}$ is a $(m\times 1)$ vector of unknown parameters; ξ_i, represents symmetric random error and is assumed to be independently and identically distributed (i.e., $iid\ N \sim (0, \sigma_\xi^2)$; τ_i, is asymmetric and non-negative random error and is obtained by truncation at zero from below the normal distribution with mean μ and variance σ_τ^2 (i.e., $iid\ N (\mu, \sigma_\tau^2)$).

The typical inefficiency effects model is given by

$$\tau_i = z_i\delta + \omega_i = \mu_i + \omega_i \qquad (2)$$

where, ω is a random variable assumed to be truncated from a normal distribution, $N \sim (0, \sigma^2_\omega)$; the point of truncation is $-z_i\delta$, and it maintains the condition, $\omega_i \geq -z_i\delta$ for a positive value of τ_i; where, $z_i = (z_{1i}, z_{2i}, \ldots z_{ki}) \geq 0$, and δ is a $(k\times 1)$ vector of unknown coefficients.

Estimation of a stochastic frontier model

The Maximum Likelihood (ML) is popular analytical tool for estimating frontier models since it (ML) has some advantages over the ordinary least square (OLS) method and its variants (see Coelli, 1995; Gujarati and Sangeetha, 2007, p. 116, 120; Coelli et al., 2005, p. 245). In order to comply with the ML method each of the two random errors (ξ_i and τ_i) of a stochastic frontier must have a distributional specification. However, intricacy lies with the distributional specification of the one-sided non-negative technical inefficiency component that it can assume several distributional specifications, namely, half normal, truncated normal, exponential and gamma; although the first two types are very popular. Indeed, the truncated-normal is a more logical distributional specification (Stevenson, 1980) and has widely been applied in empirical works (see Rouf, 2015; Rahman et al., 2009; Wadud and White, 2000; Dawson and Lingard, 1991). In the case of a half-normal specification, it is assumed that the one-sided error term, τ, is distributed with a half normal density, having a mode of $\tau = 0$. Stevenson (1980) argues that since production activities are conducted by human beings, the likelihood of a non-zero mode (mean) for the inefficiency component τ is more tenable. In line with Stevenson's (1980) argument, it can be contended that the likelihood of having a non-zero mean for inefficiency effects (τ), in a developing country agriculture is much higher than that in a developed country agriculture because of its highly mechanised agriculture. Thus, a stochastic frontier model having normal-truncated normal distributional specifications more appropriately represents the production environment in developing country agriculture.

Estimation of a normal-truncated normal stochastic frontier model involves calculation of density functions at different levels and ends up with the conditional density of τ with respect to ε (See Kalirajan and Shand, 1986; Kumbhakar and Lovell, 2000). The ratio of the marginal density of ε to the joint density of τ and ε, provides the conditional density of τ, which is given by

$$f(\tau/\varepsilon) = \frac{1}{\sigma_* \sqrt{2\pi}} . exp\left[-\frac{(\tau-\mu_*)^2}{2\sigma_*^2}\right] / \left[\left(1-\Phi(-\frac{\mu_*}{\sigma_*}\right)\right] \tag{3}$$

where, $\mu_* = (-\sigma^2_\tau \varepsilon + \mu\sigma^2_\xi)/\sigma^2$ and $\sigma^2_* = \sigma^2_\tau \sigma^2_\xi / \sigma^2$. The mean of the conditional distribution $N^+ (\mu_*, \sigma^2_*)$, is used as a point estimator of τ_i and is given by

$$E(\tau_i|\varepsilon_i) = \mu_{*i} + \sigma_* \left[\frac{\varphi(-\mu_{*i}/\sigma_*)}{1-\Phi(-\mu_{*i}/\sigma_*)}\right] \quad (4)$$

In order to obtain the estimate E (τ_i | ε_i), i.e., $\hat{\tau}_i$ the unknown parameters, μ_* and σ_*, are to be estimated.

Prediction of technical inefficiency

There are two types of measurements for predicting technical inefficiency effect with a production system: output-orientated and input-orientated. However, the output-oriented measurement is popular because it has some advantages over the input-oriented measurement. The main advantage of output-oriented measurements is that it involves a relatively smaller number of variables in the estimation process unlike the input-oriented measurements; moreover, output figures are more easily observable than input variables. Furthermore, it is more convenient to estimate the potential level of output compared to that of inputs. Considering the above advantages and importantly, for the sake of availability of data, one may argue that output-oriented measurement fits the developing country agriculture. This is because of the fact that farmers in the developing countries do not maintain a record of the input-output data unlike the developed country farmers, and when asked for data they (farmers in developing countries) provide it from their memory. This study, however, follows the output-oriented measurement for the empirical study of two competing interventions involving rice production. The measure of output-oriented technical efficiency (TE), it is the ratio of observed output (y_i) to the corresponding frontier output, y_i^*. So the technical efficiency of the i-th production unit is

$$TE_i = \frac{y_i}{y_i^*} = \frac{Observed\ \ output}{Stochastic\ \ frontier\ \ output} = \frac{y_i}{exp\ (x_i'\beta + \xi_i)}$$

$$= \frac{exp\ (x_i'\beta + \xi_i - \tau_i)}{exp\ (x_i'\beta + \xi_i)} = exp(-\tau_i) \quad (5)$$

According to Battese and Coelli's (1988) formulation, technical efficiency is the expected value of [exp $(-\tau_i)$]. Thus

$$TE_i = E\{\exp(-\hat{\tau}_i)\,|\,\varepsilon_i\} \tag{6}$$

$$= \left[\frac{1-\Phi\left(-\frac{\mu_*}{\sigma_*}+\sigma_*\right)}{1-\Phi\left(-\frac{\mu_*}{\sigma_*}\right)}\right].\exp\left(-\mu_{*i}+\frac{\sigma_*^2}{2}\right) \tag{7}$$

The difference between y_i and y^* is reflected by τ_i ; so, y_i is equal to y_i^*, when $\tau_i = 0$, meaning, technical efficiency, $TE_i = 1$. If $\tau_i > 0$, the production function will lie below the frontier, $TE_i < 1$, i.e., the production unit is technically inefficient. On the other hand, the key features of technical inefficiency are expressed by two crucial variance parameters, and these are parameterised as

$$\sigma_\varepsilon^2 = \sigma_\xi^2 + \sigma_\tau^2 \text{ and } \gamma = \sigma_\tau^2/\sigma_\xi^2 + \sigma_\tau^2 \tag{8}$$

(See Kalirajan and Shand, 1986)

The parameter γ is bounded between zero and one. Equation (8) indicates that the value of γ directly relates to the extent of domination of the one-sided error component on the symmetric error.

Functional forms and zero observations

The Cobb-Douglas and the traslog are the two dominant functional forms used with stochastic frontier analysis (see Darku et al., 2013; Bravo-Ureta and Pinheiro, 1993; Battese, 1992). However, quality of data may play a significant role in determining the right functional form between these two. For example, when data contains a considerable number of zero observations translog is not an appropriate functional form (Sharma, 1999; O'Neill and Matthews, 2001 and Sharma and Leung, 2000) as it generates more zero values which end up with biased estimates. The presence of zero observations is a common phenomenon in developing country agriculture where input variables may have zero values for a number of reasons. However, exclusion of the farmers who omitted any of the input items and confining the analysis to only those farmers having positive values for the input items is not an acceptable practice, because this would provide a misrepresentative picture of the reality.

Considering the reality of developing country agriculture use of Cobb-Douglas models are more appropriate for the study of productive efficiency as far as zero observations are concerned; in fact, Cobb-Douglas model has overwhelmingly surpassed the traslog model in this regard (see Bravo-Ureta et al., 2007; Thiam et al., 2001; Coelli, 1995; Battese, 1992). It is suggested that the impact of the functional form on key results of the study should be taken into account (Bravo-Ureta and Pinheiro, 1993) apart from other considerations. For example, Conradie et al., (2006) estimated both the Cobb-Douglas and translog models in the study of efficiency for grape production with different production environments in South Africa. However, comparing results from both of the models, the authors realised that the results from the Cobb-Douglas model were more consistent, which led them to accept the Cobb-Douglas model.

Comparing interventions: individual modelling vs. pooled modelling approaches

Stochastic frontiers can be modelled using two distinctive approaches for making comparisons between different types of interventions/development strategies: individual modelling and pooled modelling. Under the individual modelling approach, separate frontier models are constructed for each of the intervention and these are estimated independently to obtain efficiency scores against respective interventions; while all the individual (separate) frontier models are combined together to form a single model under the pooled modelling approach. More specifically, a pooled model is made up of data from all the production units under the interventions in consideration. After estimation of the pooled model, each of the individual models that constituted the pooled model, is separated to obtain the efficiency scores against the respective interventions. As for example, let A and B are two competing interventions to be evaluated. Under individual modelling approach, two independent frontier models (say, model-I for A and model-II for B), are developed and estimated independently; in contrast, these two individual models (i.e., model-I and model-II) are combined to form a pooled model, and after estimation these are separated to obtain efficiency scores against the respective interventions.

Howsoever, if the interventions belong to the agricultural sector it is practical to use the pooled modelling approach. The logic of developing a pooled model here is that pooled model approach provides a level playing field for the production units with all competing/alternative interventions. In other words, all the production units under consideration are assessed using a unique standard. It is, in fact, a fair way of comparing different production environments/processes. There are empirical works (e.g., Kalirajan and Shand, 1986; Kumbhakar et al., 1989; Tadesse and Krishnamoorthy, 1997; Conradie et al., 2006; Rahman et al., 2009; Van der Vlist et al., 2007) that employed pooled modelling approach for comparative evaluation of agricultural interventions/development strategies.

Methodology of the Study

Rice is the main crop produced with the two interventions. The farming practice of rice in the study area fully complies with the Zellner et al., (1966) assumption since the output can be characterised as stochastic and endogenous. So, this study estimates technical efficiency in order to evaluate the interventions. The stochastic production frontier (SPF) model is developed with the Cobb-Douglas functional form due to the presence of considerable number of zero observations in the data. Besides, zero variables are adjusted following the Battese (1997) procedure. Truncated normal distributional specification is assumed for the inefficiency effects and estimated with the maximum likelihood (ML) method using specialized software, FRONTIER 4.1, developed by Coelli (1996). Cross sectional data on rice production for the production year of 2011/12, collected from a sample of 357 households are used in this analysis. A total of 14 villages were randomly chosen out of 41, situated around the two interventions. Farm households from each sampled village were again stratified into small, medium and large groups based on land holdings, drawing on the classification used by the Bangladesh Bureau of Statistics (BBS, 2009). Using these stratification farm households from each group were chosen proportionately. From the SRM intervention a total of 205 households were taken into consideration and rest of the households from the TRM. Since the SRM covers a larger area than the TRM, the sample size is relatively higher for the SRM.

Empirical Stochastic Production Frontier and Technical Inefficiency Models for Pooled Data

$$ln\, y_i = \beta_0 + \beta_1\, ln\, x_{1i} + \beta_2\, ln\, [\max\, (x_{2i}, 1 - D_{1i})] + \beta_3 D_{1i}(x_{3i}) + \beta_4\, ln\, [\max\, (x_{4i}, 1 - D_{2i})] + \beta_5\, D_{2i}\, (x_{5i}) + \beta_6\, ln\, x_{6i} + \beta_7\, ln\, [\max\, (x_{7i}, 1 - D_{3i})] + \beta_8 D_{3i}\, (x_{8i}) + \beta_9\, ln\, x_{9i} + \beta_{10}\, D_{4i}\, (x_{10i}) + \xi_i - \tau_i \qquad (9)$$

where, '*ln*' indicates to a natural logarithm, and subscript *i (i- 1, 2, 3, . . . n)* refers to the i-th sample farm. y_i is output (kg) of the i-th farm; x_1, x_2, x_4, x_6, x_7 and x_9 represents respectively the cost (tk) of seed, quantity (litre) of diesel used for dewatering rice farm, cost (tk) for land preparation, amount (kg) of chemical fertilizers applied, quantity (litre) of diesel used for irrigation, amount of labour (number of man-days) applied; x_3, x_5, x_8 and x_{10} indicates the dummies for dewatering, land preparation, irrigation and interventions in consideration; while, D_1 assumes value 'One' if cost for dewatering is positive, and 'Zero', otherwise; D_2 assumes value 'One' if cost for land preparation is positive, and 'Zero', otherwise; D_3 assumes value 'One' if cost for irrigation is positive, and 'Zero', otherwise; D_4 assumes value 'One' if the intervention is SRM, and 'Zero', otherwise. (The notations 'kg' and 'tk' respectively mean kilogram and taka (Bangladeshi currency) and the measurements are taken against per acre of land.

Model for Technical Inefficiency

$$\tau_i = \delta_0 + \delta_1 z_{1i} + \delta_2 z_{2i} + \delta_3 D_{5i}\, (z_{3i}) + \omega_i \qquad (10)$$

where z_1, z_2 and z_3 present education of the farm operator, years of experience of the farm operator and ownership status of the farm respectively. Dummy D_5 assumes value 'One' if farm operator is the owner of the farm and 'Zero', otherwise.

Results and Discussions

Hypothesis Testing

A model for technical inefficiency can only be estimated if the technical inefficiency effects, τ_i, are stochastic and have particular distributional properties (Coelli and Battese, 1996). The following four hypotheses are very crucial for technical efficiency estimation with the stochastic frontier models.

H_0: $\gamma = \delta_0 = \delta_1 = \delta_2 = \delta_3 = 0$, specifies that the inefficiency effects are not present in the frontier model. If it is rejected, the traditional average response model (OLS) is not adequate for the frontier model. H_0: $\gamma = 0$, says that the inefficiency effects are not stochastic. If it is rejected the stochastic frontier is the appropriate model. H_0: $\delta_0 = \delta_1 = \delta_2 = \delta_3 = 0$, indicates that the intercept and all the coefficients of farm-specific variables are zero. That means technical inefficiency effects have a traditional half-normal distribution (with a mean equal to zero). Finally, (H_0: $\delta_1 = \delta_2 = \delta_3 = 0$), states that coefficients of all the explanatory variables in the inefficiency model are zero, which implies that the combined effect of the three inefficiency variables on production is insignificant, although the individual effects of one or more of the variables may be statistically significant (see Battese and Coelli, 1995).

These hypotheses tests are preferably carried out by the likelihood ratio (LR) statistic which is based on restricted and unrestricted models of the SFA. The generalized likelihood ratio test statistic, λ, is calculated as

$$\lambda = -2\ [\ln\{L(H_0)\} - \ln\{L(H_1)\}] \quad \sim \chi^2_r \tag{11}$$

where, $L(H_0)$ and $L(H_1)$ denote the values of log-likelihood functions under the null and alternative hypotheses respectively.

Table 1 : Hypothesis testing for the stochastic frontier pooled model

Null hypothesis	Log-likelihoods	Test statistic	Critical value (5%)	Decision
H_0: $\gamma = \delta_0 = \delta_1 = \delta_2 = \delta_3 = 0$	59.868	12.242	10.371	Rejected
H_0: $\gamma = 0$	62.99	5.998	5.138	Rejected
H_0: $\delta_0 = \delta_1 = \delta_2 = \delta_3 = 0$	61.133	9.712	9.488	Rejected
H_0: $\delta_1 = \delta_2 = \delta_3 = 0$	62.981	6.016	7.815	Accepted

Note: The critical values regarding the variance parameter γ are taken from Table 1 of Kodde and Palm (1986).

These hypotheses tests (table 1) provide several implications that stochastic frontier model is adequate for the efficiency analysis of rice production with the SRM and the TRM interventions at the first place; then the inefficiency effects are stochastic justifying the use of a stochastic frontier model with inefficiency effects. Rejection of the third null hypothesis implies that truncated normal is the right distributional specification for technical inefficiency effects. Finally, technical inefficiency effects are not a linear function of the inefficiency variables; meaning, individual effects of some of the variables may be statistically significant.

Table 2: Maximum-Likelihood Estimates of the Frontier Pooled Model

Variables	Notations	Parameters	Coefficients	Std. errors	t-ratio
Constant		β_0	1.4308	0.3438	4.1613***
Seed	x_1	β_1	0.1227	0.0363	3.3776***
Dewatering	x_2	β_2	-0.0268	0.0207	-1.2961
D_1	x_3	β_3	0.1256	0.0824	1.5250
Land prep	x_4	β_4	0.0210	0.0223	0.9444
D_2	x_5	β_5	0.1526	0.1760	0.8674
Fertilizers	x_6	β_6	0.1603	0.0400	4.0045***
Irrigation	x_7	β_7	0.0034	0.0169	0.2010
D_3	x_8	β_8	0.0076	0.0531	0.1423
Labour	x_9	β_9	0.1185	0.0549	2.1598**
D_4	x_{10}	β_{10}	0.1418	0.0380	3.7318***
Inefficiency Model					
Constant		δ_0	0.4641	0.0783	5.9285***
Education	z_1	δ_1	-0.0084	0.0043	-1.9749*
Experience	z_2	δ_2	0.0037	0.0021	0.98752
Ownership dummy D_5	z_3	δ_3	0.0137	0.0290	0.4710
Model Diagnostics					
sigma-squared		σ^2	0.0498	0.0063	7.92287***
gamma		γ	0.8954	0.1016	8.8130***
Log-Likelihood			65.9890		

*Note: *** significant at 1% level (p<0.01)*
*** significant at 5% level (p<0.05)*
** significant at 10% level (p<0.10)*

Source: Own estimation

The mean technical efficiency scores obtained for SRM and TRM interventions are 0.695 and 0.707 respectively. The range of scores for SRM, lies between 0.408 and 0.970 with a standard deviation of 0.126, while the range for TRM is 0.447 and 0.953 respectively, having a standard deviation of 0.118. These results show that overall the interventions are closer to each other with respect to technical efficiency scores.

Table 3: Frequency distribution and percentage share of technical efficiency (TE) scores by 5% and 10% class intervals

Particulars	Frequency				Percentage share			
	SRM Intervention		TRM Intervention		SRM	TRM	SRM	TRM
Ranges of TE scores	Class interval		Class interval		Class interval		Class interval	
	5%	10%	5%	10%	5%	5%	10%	10%
Below 0.50	13	13	3	3	6.34	1.97	6.34	1.97
0.50 - >0.55	14	36	10	24	6.83	6.58	17.56	15.79
0.55 - >0.60	22		14		10.73	9.21		
0.60 - >0.65	26	61	26	55	12.68	17.11	29.75	36.18
0.65 - >0.70	35		29		17.07	19.08		
0.70 - >0.75	29	48	14	33	14.15	9.21	23.42	21.71
0.75 - >0.80	19		19		9.27	12.50		
0.80 - >0.85	19	37	16	26	9.27	10.53	18.05	17.11
0.85 - >0.90	18		10		8.78	6.58		
0.90 - >0.95	9	10	10	11	4.39	6.58	4.88	7.24
0.95 and over	1		1		0.49	0.66		
Total	205		152		100.00	100.00	100.00	100.00

Source: own estimation

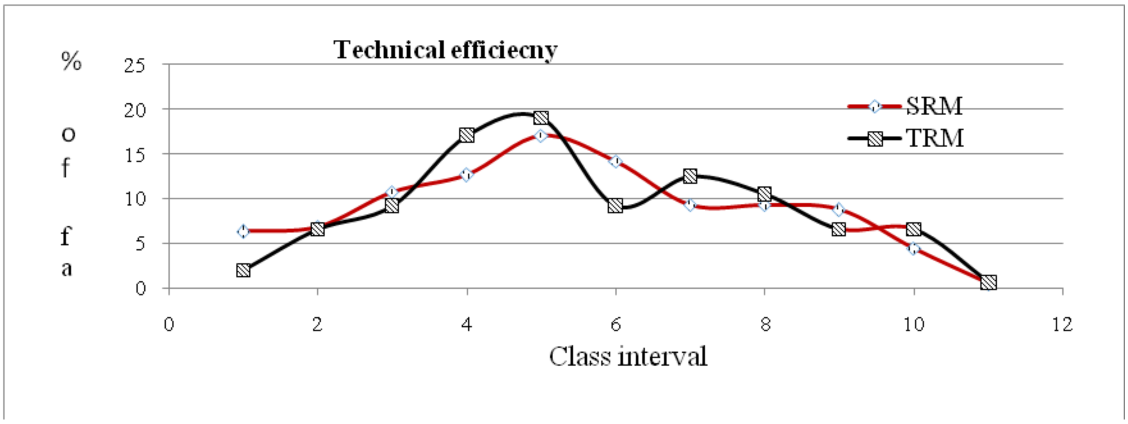

Figure 1: Patterns of score for technical efficiency by intervention

However, if farms are grouped on the basis of technical efficiency scores by class intervals, there appear some contrasting pictures between the SRM and TRM interventions. It is evident from table-3 and figure-1 that relatively higher percentage of farms belonging to the TRM intervention records a high range of efficiency scores; while a contrary picture is seen for the score range of below 0.60. These findings indicate that the TRM intervention performs better than the SRM as far as rice production is concerned. The above results obtained from the pooled model reflect the existing situation and confirm the reports of other studies (e,g., IWM, 2005; ADB, 2007; CEGIS, 2007) that the TRM intervention provides sustainable and low-cost production environment for rice production compared to SRM intervention.

On the other hand, it is of interest to check the results from the individual models along with their goodness of fit regarding the model diagnostics. The individual models come up with unrealistic outcomes; none of the individual models has both the model diagnostics (e.g., σ^2 and γ) statistically significant, which clearly contradicts with the theme of stochastic frontier analysis. Besides, the mean technical efficiency scores are excessively high considering the state of agriculture of the study area. These scores are 0.86 and 0.98 for SRM and TRM respectively. In fact, it is hard to believe that mean technical efficiency of rice production is 0.98 where farmers still skip input items. On the other hand, the pooled model with translog functional form comes up with very poor outcomes; none of the variable in the inefficiency model is significant while a few of the explanatory variables are statistically significant.

Conclusions

Estimation of productive efficiency with stochastic frontier model towards performance evaluation of an intervention in agriculture requires considering the reality of the production environment since it matters in choosing an appropriate methodological package in terms of features of the frontier model and analytical approaches. It is very unlikely that a specific combination of the features of the frontier model and analytical approach would represent different situations adequately. Likewise, there are some specifications relating to the stochastic frontier model and its methods of estimation that apply to the developing country agriculture. With reference to the empirical study, it can be contended that frontier pooled model provides consistent estimates with significant model diagnostics, unlike frontier individual models. On the other hand, Cobb-Douglas functional form of the frontier model comes up with unbiased estimates having a well fit model, unlike the translog form.

Recommendations

Estimation of productive efficiency involves a sophisticated way of comparison between observed and potential data based on the likelihood of a host of factors relating to production units and management affairs, while a few of these factors are actually taken into consideration. Hence estimates may appear highly sensitive to any of the features of the stochastic frontier model or any aspect of estimation technique. It is, therefore, pragmatic to synthesise the estimated results with the real world situations; if these are found consistent, then one can rely on the outcomes as well as the analytical approaches.

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