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Technical efficiency: A study of smallholder rice farmer in Kilombero district, Tanzania

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Abstract. Smallholder farmers form the vast majority of rice producers in Tanzania. Nonetheless, smallholder production is known to exhibit inefficiency in production. This study sought to analyze the determinants of technical efficiency of production of smallholder rice farmers in Tanzania using the stochastic frontier method while ensuring theoretical consistency through monotonicity and quasi concavity checks. Results show that empowerment of the woman, gender, primary occupation, group membership of household head and fertilizer use by the household affect technical efficiency of production.
Keywords. Technical efficiency (TE), TE scores, Monotonicity, Determinants, Tanzania.
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1. Introduction

Farrell (1957) defines efficiency as a firm's success in producing an output as large as possible from a given set of inputs. In crop production, Mango *et al.,* (2015) argue that efficiency refers to the efficient use of farm inputs. Agricultural farms can therefore use more or less inputs and still arrive at the same level of output. The differences in employed inputs can be removed if the less efficient farms adopt the practices of the more efficient farms. The concept of technical efficiency is defined relative to the best performing farm (O'Neill *et al.,* 1999; Minviel & Latruffe, 2017; Manevska-Tasevska *et al.,* 2013). To obtain a farm's technical efficiency (TE), one can calculate actual achievable output and divide it by maximum achievable output using a number of approaches that have been recommended by scholars in the field (Shih *et al.,* 2004; Lambarraa *et al.,* 2007).

Farrell (1957) recommended two distinct methods in the estimation of technical efficiency; i) the non-parametric approach with theoretical underpinnings of linear optimization and, ii) the parametric method which assumes a particular functional form and allows for hypothesis testing. According to Battese & Coelli (1988), the unit isoquant defines the input-per-unit-of-output ratios associated with the most efficient use of the inputs to produce the output involved. Battese & Coelli (1988) further consider the deviation of observed input-per-unit-of-output ratios from the unit isoquant to be associated with technical inefficiency of the firms involved.

2. Models and estimation procedure

2.1 The stochastic production frontier

Smallholder farming production behavior can better be modeled by the stochastic frontier model due to its heavy dependence on natural conditions that are not under control of the farmers and the existence of measurement errors (Kidane & Ngeh, 2015), moreover, data from smallholder farmers remains largely inaccurate (Carletto *et al.,* 2015); smallholder farmers often do not keep books of

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accounts and therefore may provide inaccurate varying information in which case the stochastic Production Frontier proves quite useful (Nchare, 2007).

Within the stochastic production frontier first proposed by Aigner *et al.,* (1977) and Meeusen & Van den Broeck (1977), the possible production is bounded above by the stochastic quantity;

$$Y_i \leq f(x_i;\beta)+(v_i) \qquad for \quad i=1,2,...N \tag{1}$$

The Stochastic production frontier above starts with the error term decomposed into its two components below;

$$\varepsilon_i \quad \leq v_i + u_i \quad i-1,...,N \tag{2}$$

The error component v_i represents the symmetric disturbance: the $\{v_i\}$ are assumed to be independently and identically distributed as $N(0,\sigma^2)$. The error component u_i is assumed to be distributed independently of v_i, and u_i is intended to capture the effect of technical inefficiency. Producers thus produce on or below their stochastic production frontier thus $u \leq 0$. It is equal to zero if the farmer produces on the frontier and it is less than zero if the farmer produces below the frontier. Meeusen & van den Broeck (1977) in Battese (1992) assigned an exponential distribution to u, Battesse & Corra (1977) assigned a half normal distribution while Aigner *et al.,* (1977) gave a critique of either assumptions about u and considered both distribution assumptions. Either distributional assumption implies that the composed error term $(v-u)$ is negatively skewed thus statistical efficiency requires the model to be estimated by Maximum Likelihood method (Kumbhakar & Lovell, 2003).

Studies on efficiency measurement such as Nkamleu (2004); Bravo-Ureta & Pinheiro (1997); Kalirajan (1989), regressed the predicted efficiency indices against household and farm characteristics with an intention of explaining the observed differencesin inefficiency among farms using a two-stage procedure. However, though recognized as a useful procedure, the two -stage estimation used has been faulted as inconsistent in its assumptions with regard to the independence of the inefficiency effects within the two-stage estimations. Kumbhakar *et al.,* (1991) give a critique of the two stage procedure arguing that technical efficiency might be correlated with the inputs thus resulting in inconsistencies in the estimated parameters and the technical efficiency and, standard ordinary least square (OLS) results from the second stage estimation may not be appropriate since technical efficiency (the dependent variable) is one sided. Furthermore, Coelli (1995) noted that with the two stage procedure, the inefficiency effects in the first stage are assumed to be independent and identically distributed while in the second stage, they are assumed to be a function of firm specific factors implying that they are not identically distributed. Wang & Schmidt (2002) argue that the two step procedure falls short since the model in the first step is misspecified and provide further theoretical insights into the severity of the bias problem with the two stage estimation technique thus further solidifying an argument for the one step procedure. Given the shortfalls of the two stage estimation procedure, Kumbhakar *et al.,* (1991); Coelli (1995) and Wang & Schmidt (2002) suggest a one stage estimation procedure which results in more reliable estimates.

Aside from the two-stage and one-stage estimation issue in the estimation of technical efficiency, more recent interest has been shown in the microeconomic theoretical consistency of the estimation procedure. One basis for this interest is in grounded in the guiding principles raised by Lau (1978) for the theoretical properties required by the particular economic relationship for an appropriate choice of parameters. With regard to production theory and specifically, production possibility sets, this would mean that the relationships are single valued, monotone increasing as well as quasiconcave. Sauer *et al.,* (2006) cautions that due to the free availability of easy-to-use efficiency estimation software, there has been an increase in the number of efficiency studies without a critical assessment on theoretical consistency, flexibility and the choice of the appropriate functional form. O'Donnell & Coelli (2005) and Griffiths *et al.,* (2000) raise the importance of imposing regularity conditions and argue that only the estimates obtained from the regularity-constrained models are theoretically plausible.

Attempts have been made at incorporating this theoretical concern into efficiency estimates. Henningsen & Henning (2009) suggest a three-step procedure for estimation with the incorporation of the monotonicity and quasiconcavity; moreover, they demonstrate how monotonicity of a translog function can be imposed not only locally at a single data point but regionally at a connected set (region) of data points. Other studies such as Karimov (2014); Watto & Mugera (2015) and Olsen & Henningsen (2011) have applied this methodology and results show differences between the theoretically constrained and the unconstrained models.

In light of the above developments in the modeling procedure, there is need to model technical efficiency using the three stage procedure, incorporating checks for monotonicity and quasi concavity in order to arrive at a theoretically sound conclusion about the estimated parameters.

Literature abounds with studies showing that age, family size, land ownership status, gender, agroecology, hiring of labour and environmental factors among several other variables affect technical efficiency. Studies however disagree on the direction of this effect with some having a negative while the others appearing to have a positive effect. Notably, most studies look at a host of factors in understanding the determinants of technical efficiency. These can affect technical efficiency through different pathways that are not explicitly explored in most of the studies, for example gender and extension can independently affect technical efficiency but a combination of gender-extension may have a different result in terms of effect on technical efficiency. In this case, exploring the effect of each variable and the possible interaction between these variables can give more elaborate pathways of the effects that they have on technical efficiency.

2.2. Production Frontier Analysis

The study uses the stochastic frontier analysis in estimation of technical efficiency and adopted the specification of the stochastic production in terms of the initial production values as proposed by Aigner *et al.,* (1977) below;

$$y_k = f(x_{ki};\beta_i)\exp(v_k - u_k) \tag{3}$$

Where;

y_k is potential output level from farms x_k is a vector of inputs and other farm specific explanatory variables, β is a vector of unknown parameters and $v_k - u_k$ is a two sided error term with v_k assumed to be iid N(O,σ_v^2) random errors and independently distributed of the u_k. v_k is random and not under control of the farmer such as weather changes and measurement error (Battese, 1992). u_k is a asymmetric, non-negative and reflects technical inefficiency (Dinar, *et al.,* 2007). If farmers attain maximum possible output then they are technically efficient thus u_k=0.

Given the x vector of inputs and the farms, the technical efficiency of the k^{th} farm is given as

$$TE_k = \frac{f(x;\beta)e^{(v_k - u_k)}}{f(x;\beta)e^{-u_k}} = \frac{e^{(v_k - u_k)}}{e^{-u_k}} = e^{v_k - u_k + u_k} = e^{v_k} \tag{4}$$

The score attained for technical efficiency lies between zero and one with a completely efficient firm attaining a score of one while the completely inefficient farm attains a score of zero.

Aside from the methodology, one emerging issue in the estimation of technical efficiency is the theoretical consistency of the stochastic production frontier method with regard to microeconomic assumptions of monotonicity and quasiconcavity (Sauer *et al.,* 2006).

Many studies have not taken these key properties into consideration and Henningsen & Henning (2009) argue that non-monotonicity distorts the efficiency estimates and can therefore result into misleading conclusions. Henningsen & Henning (2009) however highlight the fact that a non-quasiconcave point of the production function cannot reflect profit-maximizing behavior under standard microeconomic assumptions. They further argue that measuring technical efficiency generally assumes that producers maximize output given their input quantities rather than maximizing their profits thus concluding that there is no technical rationale for production functions to be quasiconcave.

Henningsen & Henning (2009) therefore suggest a three step procedure based on a two-step procedure by Koebel *et al.,* (2003). In the first step they suggest estimation of the unrestricted stochastic production frontier, the minimum distance function and a final stage restricted frontier.

$$\begin{aligned} \ln y &= \ln f(x,\beta) - u + v \\ E[u] &= z'\delta \end{aligned} \tag{5}$$

Where $u \geq 0$ is the level of technical inefficiency, v is statistical noise, z is a vector of variables explaining technical inefficiency and δ are the parameters to be estimated.

The unrestricted parameter of the production frontier $\widehat{\beta}$ and their covariance matrix $\sum_{\beta}$ are obtained from the estimation results.

In the second step we obtain the restricted β parameters by a minimum distance estimation

$$\begin{aligned} \widehat{\beta}^0 &= \arg\min(\widehat{\beta}^0 - \widehat{\beta})\textstyle\sum_{\beta}^{-1}(\widehat{\beta}^0 - \widehat{\beta}) \\ &s.t.\ f_i(x,\widehat{\beta}^0) \geq 0\ \forall i,x \end{aligned} \tag{6}$$

$\widehat{\beta}^0$ are the model's restricted parameters while the constraint $f_i(x,\widehat{\beta}^0) \geq 0\ \forall i,x$ is the monotonicity condition imposed on the model.

The third stage involves determination of the efficiency estimates of the farms and the determinants of technical inefficiency using a theoretically consistent production function. We estimate the frontier model below;

$$\ln y = \alpha_0 + \alpha_1 \ln \widetilde{y} - u^0 + v^0 \tag{7}$$

$$E[u^0] = z'\delta^0 \tag{8}$$

The only input variable is the frontier output of each firm calculated with parameters of the restricted model

$$\tilde{y} = f(x, \hat{\beta}^0) \tag{9}$$

The parameters of the α_0 and α_1 permit the adjustment of the restricted production frontier to;

$$y = e^{\alpha_0} f(x, \hat{\beta}^0)^{\alpha_1} \tag{10}$$

A key shortfall of the approach is that it does not involve the determination of the standard errors for the restricted parameters (Tiedemann & Latacz-Lohmann, 2013). Nonetheless, it is a straightforward procedure when compared to the Bayesian approaches (Henningsen & Henning, 2009; Karimov, 2014), which either involve complex algorithms that have some convergence problems or are complex and laborious.

2.3. The translog production function

The translog functional form is popular in stochastic frontier analysis because it satisfies the second order flexibility condition (Diewert, 1974) and also its logarithmic form enables the capture of inefficiencies by an additive term thus simplifying economic estimation (Henningsen & Henning, 2009).

We adopt the translog form defined by Henningsen & Henning (2009) as,

$$\begin{gathered}\ln y = \ln f(x, \beta) = \beta_0 + \sum_{i=n}^{n} \beta_i \ln x_i + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} \ln x_i \ln x_j + v_i - u_i \\ \beta_{ij} = \beta_{ji}\end{gathered} \tag{11}$$

The marginal products which are drawn from the first derivatives are;

$$f_i = \frac{f(x, \beta)}{x_i} \left(\beta_i + \sum_{j=1}^{n} \beta_{ij} \ln x_j \right) \tag{12}$$

The second derivatives are;

$$f_{ij} = \frac{f(x, \beta)}{x_i x_j} \left(\left(\beta_i + \sum_{k=1}^{n} \beta_{ik} \ln x_k \right) * \left(\beta_j + \sum_{k=1}^{n} \beta_{jk} \ln x_k - \Delta_{ij} \right) - \beta_{ij} \right) \tag{13}$$

Where;

$\Delta_{ij} = 1$ if $i = j$ and $\Delta_{ij} = 0$ otherwise.

And below are the dependent and independent variables used in the translog function;

$y = \ln Output$

$x_1 = \ln Plotsize$

$x_2 = \ln Labour$

$x_3 = \ln Seed$

$x_4 = \ln Plot^2$

$x_5 = \ln Plotsize * \ln Labour$

$x_6 = \ln Plotsize * \ln Seed$

$x_7 = \ln Labour^2$

$x_8 = \ln Labour * \ln Seed$

$x_9 = \ln Seed^2$

The study uses calculations within the “R software environment for statistical computing and graphics” (R Developemnt Core Team, 2009) using the R package “frontier” developed by Coelli & Henningsen (2017), “micEcon” (Henningsen, 2017), “quadprog” (Turlach, 2013) and “car” (Fox, *et al.,* 2017) to estimate the initial unrestricted stochastic frontier, the latter restricted stochastic frontier and the subsequent likelihood ratio test. In the second stage, monotonicity is imposed by solving a quadratic optimization model. Monotonicity is imposed on parameters via the asymptotically equivalent minimum distance estimator, together with the parameters of the production frontier, $\hat{\beta}$, and their covariance matrix, $\hat{\Omega}_{\beta}$, which are extracted from the first step. Monotonicity restriction is imposed in order to ensure theoretical consistency of the estimation and indeed there is a change in the model coefficients between the unrestricted and the restricted models.

3. Results and discussion of results

3.1. Descriptive results

The data used in this study was collected using a household survey conducted conducted by AfricaRicein August 2016 from 5 villages in Kilombero district, Tanzania namely Njage, Mbingu, MsolwaUjamaa, Mang’ula A and Mkula. From the total responses, data from 256 households has been adopted for use in the analysis for this chapter.

With missing values and non-response, the remaining effective sample upon which the technical efficiency analysis was based was 200. Table 1 gives a description of the sample from which the data was drawn.

Table 1. *Descriptive Results for Variables Used in Analysis*

	Mean (Std. Dev)	Minimum	Maximum
Socio economic variables			
Age	49 (12)	21	80
Gender of hh head (1= Male)	0.49 (0.50)	0	1
Education (1=Attained atleast primary educ)	0.69 (0.46)	0	1
PrimaryActivity (1=Non Farm)	0.19 (0.39)	0	1
Empowerment of the women (1= Empowered in 60 %))	0.40 (0.49)	0	1
Marketing of rice(1=Marketing)	0.79 (0.41)	0	1
Accessing extension (1=Accessing)	0.70 (0.46)	0	1
GrowingimprovedSeed (1=Improved)	0.46 (0.50)	0	1
Growing in Irrigated Ecology (1=Irrigated)	0.35 (0.48)	0	1
ApplyingFertilizer	0.47 (0.50)	0	1
		Production Variables	
Production in Kg	1726 (1407)	2	5000
Plot size in acres	2.1 (1.4)	0.25	10
Seed in Kg	46 (42)	2	300
Labour (No of people)	26 (14)	2	50
FertilizerUsed (Kg)	69.3 (55.7)	1	275

From Table 1, average age was 49 years old with the oldest farmer being 80 years and the youngest 21 years of age. Forty nine percent of the sampled farmers were male, 69 percent had attained at least a primary education, 19 percent practiced alternative non-farm activities as primary activities for income generation. In examining the level of women empowerment in the sampled households, 40 percent of the households had women that reported empowerment in atleast 60 percent of the weighted domains. Seventy nine percent of the sample reported marketing rice produce.

In terms of the production variables, the mean level of production was 31,726 kilograms, average acreage of 2.1 acres, average seed used was 46 Kg and average labour of 26 persons. Forty six percent of the sampled farmers grew improved varieties and 35 percent grew paddy in irrigated ecologies.

3.2. Technical efficiency scores and model estimation results for inputs and inefficiency effects

An initial estimation of technical efficiency scores for the male headed and female headed households using a single frontier shows the distribution of the scores in Table 2for the two household types (male and female headed households).

Table 2: *Technical Efficiency Attainment: Male Headed versus Female Headed Households*

		Male HeadedHouseholds		FemaleHeadedHouseholds	
No.	TE Range	Frequency (n=97)	Mean (StdDev)	Frequency (n=103)	Mean (StdDev)
1	0 to 0.1	3	0.0540 (0.0251)	8	0.0325 (0.0203)
2	0.11 to 0.2	0	-	7	0.1610 (0.0355)
3	0.21 to 0.3	2	0.2613	5	0.2700 (0.0409)
4	0.31 to 0.4	2	0.3666 (0.0204)	8	0.3616 (0.0325)
5	0.41 to 0.5	8	0.4534 (0.0230)	18	0.4569 (0.0295)
6	0.51 to 0.6	14	0.5668 (0.0315)	19	0.5567 (0.0373)
7	0.61 to 0.7	20	0.6572 (0.0271)	17	0.6612 (0.0302)
8	0.71 to 0.8	22	0.7600 (0.0331)	17	0.7506 (0.0295)
9	0.81 to 0.9	26	0.8308 (0.0158)	4	0.8384 (0.0124)
	Total	97	0.6644	103	0.5012

Note: The overall means for male headed and female headed households are statistically significantly different at 1%

Above table results are from own computation of a single production frontier using R-Codes by Henningsen & Henning (2009).

For technical efficiency scores overall mean for the male headed households is 0.6644 and is higher than that of the female headed households whose overall average is 0.5012.

These results are contrary to those of Koirala *et al.,* (2015) who found female headed households to have attained higher technical efficiencies and Kinkingninhoun-Mêdagbé *et al.,* (2010) in a study in Benin who found that although women had lower productivity, they were as technically efficient as men.

Furthermore, efficiency scores are generated and compared across grouping variables such as education, primary occupation, access to extension, group membership among others, the mean scores are shown in Table 3 and an assessment is done to establish whether there is a significant difference between these mean scores.

Table 3. *Group Comparison of Mean Technical Efficiency Scores*

Group	Different Groups	Mean TE Scores	Mean comparison
Education	Non educated (n=62)	0.5319 (0.0288)	***
	Attained primary educ (138)	0.6216 (0.0169)	
Occupation	Non Farm (n=38)	0.5082 (0.0465)	***
	Farming (n=162)	0.6139 (0.0145)	
Extension Access	Accessing (n=140)	0.6157 (0.0175)	**
	Not Accessing (n=60)	0.5427 (0.0276)	
Group Membership	In a group (n=73)	0.6492 (0.0249)	***
	Not in a group (n=127)	0.5620 (0.0182)	
Fertilizer Use	Using (n=106)	0.6167 (0.0184)	NS
	Not Using (n=94)	0.5680 (0.0239)	
Empowerment of the female	Empowered (80)	0.5811 (0.0194)	NS
	Not empowered (120)	0.6130 (0.0235)	
Marketing produce	Not Marketing (n=43)	0.5554 (0.0303)	NS
	Marketing (n=157)	0.6043 (0.0171)	
Improved Variety	Growing improved (n=92)	0.6100 (0.0213)	NS
	Non Improved (n=108)	0.5800 (0.0209)	

Note: ***, **, NS= Statistically significant at 1%, 5% and Not statistically significantly different

From Table 3, technical efficiency scores varied across farmer categories according to education, primary occupation, extension access and group membership; more educated farmers, those accessing extension services and those in groups reported higher technical efficiency than their counterparts. An unexpected result however is that farmers were more technically efficient than those who had alternative nonfarm occupation. This can be due to the fact that for farmers, experience enhances their ability to make optimal farming decisions as compared to those that fall behind in farming experience. Moreover Okoye *et al.,* (2016) have similar findings about occupation and argue that off-farm incomes could imply that less time is spent on the farm, and so resources are used in a less efficient way.

An attempt to disaggregate analysis by technologies applied such as according to improved versus traditional seed or modern technologies such as (tractor vs hand hoes) gave unsatisfactory results and notably, farmers did not exclusively report inclination to use of one strict technology set given that at different stages of production they alternated between using hoes, some ploughs and tractors. For those that planted improved seed, there were also reports of mixing of seeds types where they reported planting both varieties as well as recycling of seed from previous seasons which practices probably compromised the possibility of reliable results from such disaggregated analysis.

Due to the short coming in disaggregation of analysis to the different practices as a result of farmer practices, the combined data is used in technical efficiencyanalysis in terms of the inputs contributing to output and the inefficiency effects; the results of efficiency scores are as indicated in Table 4 for the unrestricted and the restricted models:

Table 4. *Distribution of Technical Efficiency Estimates for the study site from Unrestricted and the Restricted Models*

		Unrestricted model		Restricted Model	
No.	TE Range	Frequency (n=200)	Mean (StdDev)	Frequency (n=200)	Mean (StdDev)
1	0 to 0.1	11	0.0383 (0.0241)	12	0.0440 (0.0290)
2	0.11 to 0.2	7	0.1382 (0.0178)	6	0.1593 (0.0390)
3	0.21 to 0.3	7	0.2675 (0.0366)	4	0.2660 (0.0220)
4	0.31 to 0.4	10	0.3626 (0.0295)	11	0.3653 (0.0340)
5	0.41 to 0.5	26	0.4558 (0.0273)	24	0.4587 (0.0264)
6	0.51 to 0.6	33	0.5610 (0.0348)	30	0.5503 (0.0284)
7	0.61 to 0.7	37	0.6590 (0.0282)	45	0.6563 (0.0284)
8	0.71 to 0.8	39	0.7558 (0.0315)	37	0.7550 (0.0265)
9	0.81 to 0.9	30	0.8318 (0.0154)	31	0.8276 (0.0149)

Source: Author's estimation using "frontier" package in R software using codes by Henningsen & Henning (2009). Mean unrestricted is 0.5803 and for the restricted is 0.5861

From the combined data, initial parameter estimates of the unrestricted model in translog form of the production function are indicated in Table 5.

Table 5.1 *Estimates from the Unrestricted Translog Production Function*

Variable	Parameter	Coefficient	Std. error	Z value
Constant	β_0	5.5567**	1.9799	2.8066
Ln(plot size)	β_1	-0.4603	1.1770	-0.3911
Ln(labour)	β_2	1.2091*	0.5708	2.1183
Ln(Seed)	β_3	-0.1663	0.7950	-0.2092
Ln(Fertilizer)	β_4	-0.2008	0.1842	-1.0901
(Lnplot)^2	β_5	0.3616	0.4453	0.8120
(Lnlabour)^2	β_6	-0.1266	0.1017	-1.2444
(LnSeed)^2	β_7	0.2944	0.3042	0.9678
Ln(Fertilizer)^2	β_8	0.0414	0.0500	0.8287
LnPlot*LnLabour	β_9	0.0600	0.2449	0.2450
LnPlot*LnSeed	β_{10}	-0.1288	0.3153	-0.4087
LnPlot*LnFertilizer	β_{11}	-0.0448	0.0645	-0.6940
LnLabour*LnSeed	β_{12}	-0.1610	0.1604	-1.0039
LnLabour*LnFertilizer	β_{13}	0.0152	0.0392	0.3871
LnSeed*LnFertilizer	β_{14}	0.0629	0.0525	1.1906
SigmaSq	σ^2	2.3797***	0.7830	3.0390
Gamma	γ	0.7312***	0.1140	6.4146

Source: Author using frontier package in R software using codes by Henningsen & Henning (2009)[1]

From *table 5*, σ^2 is the total variance $(\sigma_u^2 + \sigma_v^2)$ and γ is the proportion of the variance of technical inefficiency in the total error variance (σ_u^2 / σ^2). The β_s are defined as those parameters affecting output. Gamma is equal to 0.73 and significant at 1%, which indicates that much of the variation in the composite error term is due to the inefficiency component.

The primary input labour has a significant effect on output thus an increase in the amount of labour results in an increase in the level of output given the current level of other inputs. This is an expected result given that smallholder rice farming is labour intensive activity (Mdemu & Francis, 2013). In testing the null hypothesis of no inefficiency effect, the null hypothesis is rejected thus implying that the joint effect of the explanatory factors significantly contribute to technical efficiency. This is because the value of gamma is relatively high (0.73) and highly significant thus indicating that much of the variation in output is not directly due to changes in the level of fixed inputs only but rather is due to changes in capacity utilization thus the analysis of socio-economics aspect of smallholder farmers is more suitable in explaining the existing variation in technical efficiency.

Therefore from the unrestricted model, Table 6 indicates the results of the determinants of technical efficiency.

Table 6. *Determinants of Technical Efficiency from the Unrestricted Translog Production Function*

Variable	Parameter	Coefficient	Std. Error	z-value
Empowermentat 60%	δ_1	-1.4235*	0.7611	-1.8704
Age	δ_2	0.0582	0.0445	1.3085
Age squared	δ_3	-0.0005	0.0006	-0.8238
Gender of household head(1=Male)	δ_4	-2.2713**	1.0941	-2.0758
Fertilizer use (1=Fertilizer use)	δ_5	-2.4855**	1.0240	-2.4272
Education of household head(1=attained primary)	δ_6	-1.3394**	0.6654	-2.0128
Primary occupation of hh head (1=Non Farm)	δ_7	3.5538***	1.2661	2.8069
Marketing riceproduce (1=Marketing)	δ_8	0.6834	0.7614	0.8976
Extension access (1=Accessing extension)	δ_9	-0.3181	0.5181	-0.6404

Growingimprovedvarieties (1=Improved)	δ_{10}	-0.6437	0.5943	-1.0831
Irrigating (1=Irrigating)	δ_{11}	0.2219	0.7278	0.3049
Group membership (1=Holdmembership)	δ_{12}	-2.0527**	1.9848	-2.0845

Source: Author's estimation using "frontier" package in R software using codes by Henningsen & Henning (2009).

From Table 6 the δ_s are those parameters affecting technical inefficiency. In interpreting the results of the inefficiency model, positive parameter estimates for the *z*-variables are interpreted as a positive relationship between the *z*-variables and the inefficiency term, *u* (Olsen & Henningsen, 2011). Notably, empowerment of the woman within the household, fertilizer use, gender, education, primary occupation and group membership of the household head are significant in their effect on technical inefficiency of the household.

Although fertilizer use has been argued by studies such as Abebe (2014) to indicate improvement in technology, or as an input in production such as by Geta *et al.,* (2013), Chirwa (2007) analyzes fertilizer as an improvement in technology but also examines it as one of the inefficiency effects; it is found to have an insignificant effect on technical efficiency thus cautioning that although some farmers had adopted fertilizer technology, given the low level of education among most farmers and the small land holdings, such technologies may be applied inappropriately.

In the test of monotonicity condition, we find that monotonicity for individual inputs reveals that for "plot size" monotonicity is fulfilled in 90 percent of observations; for labour it is fulfilled for 98.5 percent while the variable with monotonicity fulfilled in the least number of observations is "seed" at 56 percent and for fertilizer at 46 percent. For plot size and labour the level of monotonicity achieved is acceptable even as Henningsen & Henning (2009) suggest that if the monotonicity condition is violated only at a few data points, these are probably random deviations from the ‘‘true’’ monotonically increasing production frontier and they suggest imposing the monotonicity condition in the estimation. For seed, monotonicity is achieved in less than half the observations. Although our data does not provide evidence of this, one possible reason for the result on monotonicity of seed can be explained by the difference in crop establishment method thus differences in seed rate that translates into different levels of output (farmers traditionally broadcast seed at 30Kg per Ha but under the recently introduced SRI (System of Rice Intensification) some plant 6-7 Kg per Ha). Some farmers plant in the nursery bed and then transplant seedlings later while others directly sow by planting in lines. A high seed rate through broadcasting may not necessarily result in high output due to the compromise in the vigour of viable crops while those planting in lines or transplanting may have a low seed rate but harvest higher levels of output thus for a section of the observations, monotonicity may not be observed. For fertilizer, while some farmers applied in the nursery, others applied fertilizer in the rice fields after crop establishment yet still others applied no fertilizer at all.

In the second stage of analysis, we obtained the coefficients by the minimum distance estimation which Kumbhakar (2006) describes as adopting an input-saving approach to the measurement of the distance from a producer to the boundary of production possibilities and the results are presented in Table 7;

Table 7. *Minimum Distance Results*

	Parameter	Coef (min Dist Result)	Diff	diff/std.err	Adj.coef*
Constant	β_0^0	5.4989	-0.0578	-0.0292	5.5721
lnPlot	β_1^0	-0.0810	-0.3793	-0.3223	0.0807
lnLabour	β_2^0	0.8100	-0.39991	-0.6992	0.7944
lnSeed	β_3^0	-0.0465	-0.1198	-0.1507	-0.0457
lnFertilizer	β_4^0	0.0000	-0.2008	-1.0901	0.0000
(lnPlot^2)	β_{11}^0	0. 1614	0.2002	0.4496	0.1583
(lnPlot*lnLabour)	β_{12}^0	-0. 6667	1.2668	5.1727	-0.0654
(lnPlot*lnSeed)	β_{13}^0	0.0387	-0.1676	-0.5316	0.0379
(lnPlot*lnFertilizer)	β_{14}^0	0.0000	-0.0448	-0.6946	0.0000
(lnLabour^2)	β_{22}^0	-0.0548	-0.0718	-0.7060	-0.0537
(lnLabour*lnSeed)	β_{23}^0	-0.0158	0.1452	0.9052	-0.0155
(lnLabour*lnFertilizer)	β_{24}^0	0.0000	0.0152	0.3878	0.0000
(lnSeed^2)	β_{33}^0	0.0177	0.2767	0.9096	0.0174
(lnSeed*lnFertilizer)	β_{34}^0	0.0000	0.0629	1.1981	0.0000
(lnFertilizer^2)	β_{44}^0	0.0000	0.0415	0.8300	0.0000

Note: *Results from step 3 estimation
Source: Author's estimation using "frontier" package in R software using codes by Henningsen & Henning (2009).

From Table 7, the change in the coefficients (minimum difference result minus unrestricted production result) is captured by the column ''diff'', but all changes are all less than two times the standard error of the first-step estimation (column ''diff/std.err'' i.e diff of minimum distance/ std error of unrestricted translog function). The last column (''adj.coef'') in the table indicates the restricted coefficients after adjusting the production frontier with α_0 and α_1 estimated in the final step. Monotonicity condition is still not fulfilled at all observations with seed exhibiting monotonicity in only 45 percent of the observations; an assessment of monotonicity of inputs indicates that; i) 'plot' is fulfilled at 199 out of 200 observations (99.5%); ii) 'labour' is fulfilled at 195 out of 200 observations (97.5%) iii) 'seed' is fulfilled at 97 out of 200 observations (48.5%). Additionally, just as with monotonicity, quasiconcavity is also not yet fulfilled in all observations and is reported as fulfilled in 26 percent of the observations.

From the last stage of estimation, the results of the final stochastic frontier showing detreminants of technical efficiency are obtained and presented in Table 8;

Table 8. *Final Stochastic Frontier Estimation: Determinants of Technical Efficiency (Step 3 Estimation*)

	Estimate	Std. Error	Z value
Intercept	0.1786	1.4221	0.1255
cFitted	0.9808***	0.1804	5.4384
Age	0.0508	0.0448	1.1343
Age squared	-0.0004	0.0006	-0.7633
Empowered at 60% (1=empowered at 60%)	-1.5838**	0.7907	-2.0029
Gender of household head (1=Male)	-2.5682**	1.1043	-2.3257
Education of household head (1=Attained primary)	-1.4046*	0.7379	-1.9035
Primary occupation of hh head (1=Non Farm)	4.0580***	1.5830	2.8956
Marketing of rice produce (1=Marketing)	0.6544	0.7989	0.8191
Extension access (1=Accessing)	-0.4728	0.6302	-0.7502
Growing improved variety (1=Growing Improved)	-0.6393	0.6242	-1.0241
Growing in irrigated ecology (1=Irrigated)	0.2095	0.8320	0.2518
Group membership (1=Has Membership)	-2.3606**	1.0409	-2.2680
Fertilizer use	-2.2577**	0.9807	-2.3023
SigmaSq	2.6805***	0.9073	2.9544
Gamma	0.7590***	0.0938	8.0956

Source: Author's estimation using "frontier" package in R software using codes by Henningsen & Henning (2009).

The intercept is not significant and the cFitted (the scaling coefficient) is one indicating the robustness of the model. Moreover, the results of the final SFA presented in table 13 above indicate the coefficient of the intercept as zero and the coefficient of the ''frontier output'' as virtually one. A closer look at the result indicates that the coefficients of the adjusted and non-adjusted restricted production frontier are almost identical (when we compare the columns ''coef'' and ''adj.coef'' of Table 8).

Noticeably while in the unrestricted model and the restricted models similar variables are significant, with the restricted (theoretically consistent) model monotonicity and quasiconcavity are reported as; i) the monotonicity condition for 'plot' is fulfilled at 200 out of 200 observations (100%); ii) for 'labour' is fulfilled at 200 out of 200 observations (100%) and iii) for 'seed' is fulfilled at 197 out of 200 observations (98.5%) and for fertilizer in 75 out of 200 observations (37.5%). In the study however, fertilizer users comprised only 47 per cent of the sample while the rest did not use fertilizer and as such monotonicity was not expected to be fulfilled in all observations especially given that we adopted a method used by Sherlund *et al.,* (2002) and Chirwa (2007) where for those not using fertilizer, a tenth of the smallest value of fertilizer used by the fertilizer users is used to estimate the model. The average efficiencies of the unrestricted and the restricted models are 0.5803 and 0.5861 respectively and therefore almost identical.

The variables affecting technical efficiency are discussed as women empowerment in atleast 60 percent of weighted domains, gender, primary occupation and group membership of household head and, fertilizer use. Women empowerment has a negative effect on technical innefficiency; these results echo the finding by Seymour (2017) in understanding the implications of women empowerment on technical efficiency in Bangladesh; the study found that reduced gender disparities within households (measured in terms of the empowerment gap between spouses) are associated with higher levels of technical efficiency, a result observed on plots women jointly manage with their spouses, as well as those that women do not actively manage. Furthermore, empowerment of women lifts the binding constraints that they face in accessing and making decisions on productive assets for example Morris & Doss (1999) observe that women face greater limitations in accessing inputs such as labour and yet from our sample labour contributes significantly to output gains. The lifting of these limitations as a result of empowerment reduces their inefficiency in production.

Male headed households are more technically efficient than female headed household. This result is consistent with findings Makate *et al.,* (2016) in a study on maize production in Zimbabwe who argued that this can be the case because planting, weeding, harvesting, and other crop management operations are labour-intensive and female farmers have relatively less access to productive resources. Additionally in terms of the labour that male and female household heads provide, Doss (2015) cautions that male and female labour may not be perfect substitutes due to social norms, skills, physical capabilities and the overall care roles that are assigned skewed towards the women. These studies raise possible reasons fro the differentials in technical efficiency attained specifically with reference to male headed households being more efficient.

With regard to primary occupation of the household head, farmers are more technically efficient than those who participate in rice farming but have an alternative non-farm primary occupation. This can be attributed to the fact that those who are primarily farmers have greater experience in farming which enhances their technical efficiency. Indeed Kalimangasi & Kalimangasi (2014) also support the view that experience has a positive effect on technical efficiency with the argument that the more experienced farmers were able to adopt new technologies in the production of cocoa. Moreover, rice farming is a labour intensive activity and requires attention to detail which may be hard to achieve for those with alternative employment although they may earn sufficient income to hire labour; Chowdhury (2016), used data for three crop seasons and cautions that family labour is more productive than hired labour with Lipton (2010) raising the argument that hired labour does require supervision by family labour. Our findings are however contrary to those of Seng (2015) in a study of effect of nonfarm activities on farm households' food consumption in rural Combodia and argues that farm households engaging in nonfarm employment tend to enjoy higher household incomes and produce agricultural products more efficiently, suggesting the vital role of nonfarm activities in raising farm households' incomes and improving farming practice.

Group membership of the household head has a negative effect on technical inefficiency thus indicating that it indeed does enhance the efficiency of smallholder rice farmers. Similar findings have been made by Bhatt & Bhat (2014) in a micro level study conducted at Jammu and Kashmir. Group membership works through the channel of easing access to productive inputs and facilitating extension linkages (Abate *et al.,* 2013). Our findings though, contradict results from Addai *et al.,* (2014) who found no significant impact of farmer based organization on technical efficiency of maize farmers across various agro ecological zones in Ghana.

Education has a negative effect on technical inefficiency thus indicating that it improves technical efficiency. Indeed Abatania *et al.,* (2012) argue that education enables farmers to interprete extension and other information thus enhancing technical efficiency. Our findings concur with those of Yegon *et al.,* (2015) in a study on soybean production in Kenya who found that education reduced technical inefficiency among farmers.

The last hypothesis that the study tests, is the suitability of the restricted model versus the unrestricted model. The study fails to reject the hypothesis that the restricted model is a preferred estimation given the likelihood ratio test that returns a p-value of 0.92. Given this result, monotonicity is a key property that should be given consideration in frontier modeling and our results have shown that empowerment of the woman within the household, gender, primary occupation, education and group membership of the household head and, use of fertilizer have significant effects on technical efficiency of production for rice producing households.

4. Concluding remarks

In conclusion, the analysis of technical efficiency of production was undertaken using the stochastic production frontier. Estimation follows a the three step procedure suggested by Henningsen & Henning (2009) that involves the unrestricted frontier, minimum distance estimation and, a final stage restricted frontierin R software using codes they developed. The restriction is done via imposing monotonicity which is meant to ensure estimation of a theoretically consistent model. Results show that the null hypothesis of no inefficiency effect is rejected thus implying that the joint effect of the explanatory factors significantly contribute to technical efficiency. Empowerment of the woman in atleast 60 percent of weighted domains, gender of the household head, primary occupation, education, and group membership of the household head and fertilizer use are significant in their effect on technical efficiency of the household.

Findings indicate that policies targeted at enhancing women empowerment, education of farmers, group membership and fertilizer use can enhance technical efficiency of smallholder rice farming households.

In the testing for monotonicity, results showed that it was violated in the inputs seed and fertilizer while nearly achieved in plot size and labour and this could be attributed to the different seed establishment methods such as nursery bed use, direct seeding and sowing in lines; it is also violated in fertilizer given the varying levels of inconsistency in application across the sample. Imposing monotonicity and estimating the restricted model improves theoretical consistency of our model with quasi concavity achieved in over 95 percent of the observations and monotonicity achieved in all the primary inputs of land and labour. Nonetheless, average efficiencies of the unrestricted and the restricted models are almost identical and are 0.5803 and 0.5861 respectively.

Suitability of the restricted model over the unrestricted model was tested and with a likelihood ratio test p-value of 0.92, the study fails to reject the hypothesis that the restricted model is a preferred estimation. Monotonicity is thus a key property that should be given consideration in frontier modeling and the results of the restricted model are more appropriate in explaining the attained technical efficiency and its determinants.

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