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Do Financial Constraints Affect Production Efficiency in Drought Prone Areas? A Case from Indonesian Rice Growers

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Introduction

Rice is a staple food in many Asian countries and accounts for around 90 percent of total production and consumption. It is an important commodity for food security as well as to receive foreign income in Asia where 250 million rice farmers reside (Hayami, 2004; Timmer, 2010). Mohanty (2013) projects that the rice consumption growth may even exceed the population growth based on the current trend in per capita rice consumption in three main countries—India, China, and Indonesia. This puts a tremendous pressure on rice production and yield in rice growing countries.

Indonesia is the third largest producer as well as one of the biggest consumers of rice in the World. Accounting for population growth and current production and consumption, International Rice Research Institute (IRRI) projects that Indonesia will require 38% more rice in the next 25 years. Despite being a major producer, food security and rice self-sufficiency are the predominant concern in Indonesia because Indonesia has been the world's 7th largest rice importer for several years, importing around 1.1 million metric tons of rice every year (FAS, USDA, 2012). Therefore an improvement in rice yield has been an important agenda in Indonesia. However, this improvement goal faces many emerging constraints such as environmental degradation, climate change, water scarcity, rising input prices, and low capital availability for rice growers.

Many biotic and abiotic factors affect the production efficiency of rice growers (Mishra et al., 2015). Greater frequency of extreme weather events such as floods and droughts is one of the important reasons for crop loss. Among abiotic stress, drought is the strongest constraint affecting nearly one third of the total rice area in Asia and causing significant economic losses to

poor rice producers (Rice Almanac, GRiSP, 2013). Crop losses are likely to be greater in the future with changing climatic conditions. With these uncertainties, a future growth in rice supplies is in shaky ground (Rice Almanac, GRiSP, 2013).

Considering the fact that there is a limited scope to expand new land frontier to increase rice production, effort should be focused on enhancing the existing farm level rice production efficiency. While technology development and adoption are important to this end, the efficient utilization of existing technology to its full potential is also equally important (Shapiro 1983; Belbase and Grabowski 1985). Kalirajan, Obwona, and Zhao (1996) argue that it will be unwise to introduce new technology if the existing technology is not being used to its full potential. Many demographic, socioeconomic, and environmental factors may influence the efficiency of rice growers.

Production performance and behavior of rice growers in abiotic stress prone areas, for example, drought prone areas may be different than those of non-affected areas. Farmers in drought prone environment have tremendous challenges in growing rice. Even if the drought tolerant variety are available, they may not be accessible for rural farmers. Additionally, for the farmers with limited or low resources, mostly the case in rural farming community in Indonesia, the adaptive capacity through irrigation infrastructure is low. Therefore the economic and financial factors may further exacerbate the vulnerability of rice growers in drought prone environments. Therefore it is interesting to analyze the economic and technical efficiency of production. Note that the economic efficiency refers to the ability of farms to utilize the best available technology and allocate resources productively and technical efficiency is related to the efficient utilization of technology.

Very few studies have analyzed the efficiency of rice growers in drought prone areas and the effect of financial factors. Mishra et al (2015) found that drought and other abiotic stress significantly affect both production and efficiency of rice growers in Bangladesh. The study found that the farmers with higher value of total assets are more efficient—indicating that wealthier farmers have better adaptive capacity. Backman et al. (2011) and Ogundele and Okoruwa (2006) have found that having access to a credit or microfinances increase the rice production efficiency in Bangladesh and Nigeria, respectively. However, these studies have not specifically focused on the effect of financial factors in the efficiency of rice growers in drought prone areas.

Additionally, most of the previous studies analyzing efficiency are based on parametric approaches where one need to assume a functional form while true functional form is unknown and then derive the inferences. To overcome this limitation, this study uses both parametric and non-parametric approach to investigate the factors affecting production and efficiency of rice growers in drought prone areas of Indonesia. Special attention is given to the role of financial variables as well as off-farm income in technical efficiency. We have presented results from both parametric and non-parametric approaches—a parametric stochastic frontier analysis and a non-parametric Data Envelopment Analysis (DEA) approach is used to estimate the model.

Literature Review

Some of the previous literature has looked at the role of financial variables in technical efficiency of rice growers in developing countries. Using quadrating stochastic frontier production function, Bäckman et al (2011) found that an access to microfinance reduces the technical inefficiency of rice production in Bangladesh. Credit helps farmers to purchase the necessary input and encourage them to adopt high yielding rice varieties during planting season

whereas it helps to maintain cash flow during growing season, as there is a time lag between purchasing the inputs and obtaining the return.

Kompas et al (2012) found that credit constraint is one of the major factors for total factor productivity (TFP) decline in rice production in many areas of Vietnam. Similarly, Duy (2012) used a stochastic frontier approach and quantile regression and found a positive effect of both formal and informal credits on production and technical efficiency of rice growers in Mekong Delta region of Vietnam. In the case of Nigeria, Ogundele and Okoruwa (2006) found that credit accessibility and farm assets positively contribute in improving efficiency of rice producers. The study used a stochastic frontier model.

Currently, in the Indonesian context, the technical efficiency of rice farming is an important concern mainly because of its important role in maintaining domestic food security as well as improving agricultural development. Brazdik (2006) has discussed the role of financing and credit program in adoption of high yielding rice varieties and hence in increase in rice productivity in 1970s and 1980s in Indonesia. Brazdik (2006) reported that easily accessible credit program allowed farmers to purchase the prescribed inputs such as seeds, fertilizers and pesticides. Using a data envelopment analysis (DEA), the study found that Indonesian farmers have 77% of technical efficiency, on average—indicating a potential to increase efficiency. In some parts of the countries such as Sumatra, Java, Kalimantan and Sulawesi, the farmers with credit constraints (having no access to credit) has lower average technical efficiency than those with no credit constraints. However, in some parts such as West Nusa and Tenggara, where majority of farmers are capable of self-financing for operating cost of rice, the study found no impact of having an access to credits on production efficiency.

Similarly, Mariyono (2014) used stochastic frontier approach to compute technical efficiency across different regions in Indonesia. The study found that rice farmers in Java and Bali, where the government support programs are promoting intensified farming and have well managed irrigation system, have the higher technical efficiency than other areas. Though the paper has analyzed the impact of different government policy and found that major variation on productivity across regions are due to differences in efficiency—suggesting a potential to improve on technical efficiency, it fails to investigate the role of credit constraints or financing ability of farmers' on rice production efficiency. Finally, one of the recent studies in Indonesia includes Heriqbaldi (2015) who used a stochastic frontier approach in estimating technical efficiency from the data from 15 provinces. The study suggested that improving farmer's income, support in financial aspects or providing economic incentives for rice growers in their productive age could increase technical efficiency because it reduces farmers' constraint in applying better inputs such as seed, fertilizer, tractor, and machinery in rice farming. Moreover, Rice Almanac, Grisp (2013) highlights that low budget for irrigation infrastructure development and inadequate capital for poor farmers are listed as important production constraint.

In summary, the above mentioned studies discussed the role of economic and financial factors in technical efficiency. However, most of the studies have limited scope in identifying and quantifying the role of generating household income such as participation in off-farm work, or easy access to credit on production and efficiency of rice farmers. Further, none of the studies have investigated about how debt affects the efficiency. Additionally, note that most of the above mentioned studies use stochastic frontier model, a parametric approach, under pre specified functional form assumption. Our study overcomes these limitations and provides an improved understanding about the role of financial and economic factors in rice production efficiency. To

do so, we use a parametric stochastic frontier model and a non-parametric DEA approach. DEA approach allows us not to pre-specify any functional form but let model fit without functional form restrictions.

Methodology

In this paper we have used both parametric and non-parametric approaches in estimating the production function and efficiency.

Parametric approach

Introduced by Aigner, Lovell, and Schmidt (1997) and Meeusen and van den Broeck (1977), stochastic frontier models have been the most common parametric approach in estimating production frontier and factors influencing efficiency. The stochastic frontier models postulate the existence of technical inefficiencies in the production process of some outputs. Typically, in assessing the efficiency, we implement two-stage approach, in which the first stage involves the specification and estimation of the stochastic frontier production function and the prediction of the technical inefficiency effects, under the assumption that these inefficiency effects are identically distributed. Based on the predicted efficiency/inefficiency scores from production frontier and using a regression model, we can investigate the factors influencing such efficiency/inefficiency.

There has been considerable research to extend and apply these models under different functional form assumptions for stochastic frontier models and under different distribution assumptions for inefficiency terms. We follow Battese and Coelli (1995) in specifying the functional form and distributional assumption. A general specification of frontier model follows:

$$y_i = f(X_i, \beta)e^{v_i - u_i} \quad (1)$$

Where y_i denotes the output of firm i, X_i is the vector of inputs for firm i, and β is the vector of unknown parameters to be estimated. The term $e^{v_i - u_i}$ denotes the error term decomposed into a symmetrical random error (v_i) and a one sided error or inefficiency term u_i. Error term v_i is assumed to be independently and identically distributed (iid) error with N (0, σ_v^2), independently distributed of u_i. The term u_i represents technical inefficiency effects and assumed to be independently distributed with truncations (at zero) of the normal distribution with mean μ_i and variance σ_u^2. Under these assumptions, the mean of technical inefficiency effects can be specified as:

$$\mu_i = \sum \delta_k z_{ik} \quad (2)$$

Where δ is the vector of unknown parameters to be estimated and Z is a vector of observable farm-specific variables hypothesized to be associated with technical inefficiency. Denoting error term factors as $\varepsilon_i = v_i - u_i$, technical efficiency can be derived from stochastic frontier model as $TE_i = \mathrm{E}[\exp(-u_i|\varepsilon_i)]$ (Battese and Coelli, 1995). Several factors are hypothesized to influence technical efficiency of rice farmers in Indonesia, including financial factors. To analyze the determinants of technical efficiency, TE_i is assumed to be a function of explanatory variables (Coelli et al., 2002) and can be obtained as follows:

$$TE_i = \delta_0 + \delta Z_i + \varphi_i \quad (3)$$

Where Z_i is the vector of explanatory variables determining technical efficiency in rice production, δ is a vector of unknown coefficients.

In order to empirically estimate the theoretical production frontier and technical efficiency models, we specify following empirical models:

$$\ln(y_i) = \beta_0 + \beta_1 \ln(Land_i) + \beta_2 \ln(Seed_i) + \beta_2 \ln(family\ labor_i) + \beta_3 \ln(Hired\ labor_i) + \beta_4 \ln[Max(Fert.\ \&\ chemical\ costs_i, 1 - D_i)] + \beta_5 \ln[Max(Bullocks\ \&\ machinary\ use\ costs_i, 1 - D_i)] + v_i - u_i \quad (4)$$

Factors influencing technical efficiency is specified as:

$$TE_i = \delta_0 + \delta_1(Age)_i + \delta_2(Education)_i + \delta_3(Financial\ constraint)_i + \delta_4(off - farm\ work)_i + \delta_5(Education * Off - farm\ work)_i + \delta_6(family\ size)_i + \varphi_i \quad (5)$$

where y_i is the total value of rice produced in farm i, Land is the total area allocated under rice crop. Other inputs such as total family and hired labor used (in man hours), fertilizer and chemical costs, and total costs for bullocks and machinery in rice cultivation are included in the production function. *D,* in equation 4 is a variable which has value one if costs are positive and zero, otherwise. In equation 5, Age represents the age and education represent the number of years of age and education of the household head, a primary decision maker in farming operation; financial constraint includes a dummy variable whether the household had problems in borrowing and having access to credit while household wanted to borrow. Off-farm work represents a dummy variable whether the household obtained any off-farm income and family size represents number of family members in the household. We have also included an interaction term between education and off-farm work.

The stochastic production function in equation (4) is a linearized version of the logarithm of Cobb-Douglas production. We estimated stochastic frontier model using maximum likelihood method and specified a truncated normal distribution for the inefficiency term. The technical efficiency effects model specified in equation (4) is estimated using a tobit regression with bootstrapped standard errors.

Non-parametric approach

Data Envelopment Analysis (DEA) measures efficiency by specifying and solving a separate linear programming problem for each firm and defining input–output vectors as tightly as possible (Boussofiane, Dyson, and Thanassoulis 1991). DEA is a non-parametric approach, which does not impose any assumption and restriction on data distribution. It measures efficiency in terms of a proportional change in inputs or outputs. We can obtain efficiency scores based on the assumption of constant returns to scale (CRS) (Charnes, Cooper, and Rhodes 1978) as well as variable returns to scale (VRS) (Banker, Charnes, and Cooper 1984) which allows to compute technical and scale efficiency for each firm.

Following Coelli et al. (2002), we assume that there are *n* farms (*n=1,.....280*) producing single output *r* (*r=1*, i.e. rice) using *k* different inputs (*k=1,2,....5*) representing land, seed, labor, chemicals & fertilizers, bullocks & machineries. For the ith farm, input and output data are represented by the column vectors x_i and y_i. The data for all *n* farms are represented by input matrix, *X* (dimension: *k X n*) and output matrix, *y (*dimension*: r X n)*. The DEA model used for calculation of technical efficiency is:

$Min_{\theta,\lambda}\theta$

Subject to $-y_i + Y\lambda \geq 0,$

$$\theta x_i - X\lambda \geq 0, \qquad (6)$$

$$N1'\lambda = 1,$$

$$\lambda \geq 0,$$

Where θ is a scalar and λ is a *n X 1* vector of constants. For VRS, convexity constraint $N1'\lambda = 1$, is added, where *N1* is a *n X 1* vector of one. The input technical efficiency score

(θ) gets a value $0 \leq \theta \leq 1$ (Coelli, et al. 2002). If the θ value is equal to 1, the farm is on the frontier and hence technically efficient.

Once we get technical efficiency under CRS and VRS, scale efficiency is calculated by the ratio $SE = \frac{TE_{CRS}}{TE_{VRS}}$. SE < 1 implies scale inefficiency that can be due to the existence of either increasing or decreasing returns to scale while SE=1 implies scale efficiency. Additionally by imposing another constraint, $N1'\lambda \leq 1$, we can obtain non-increasing returns to scale (NIRS). If $TE_{NIRS} = TE_{VRS}$ indicates DRS, $TE_{NIRS} \neq TE_{VRS}$ indicates IRS, and $TE_{VRS} = TE_{CRS}$ indicates CRS (Coelli et al., 2005).

In our paper, we estimated the input oriented technical and scale efficiencies under both CRS and VRS assumptions. Then in the second stage, the estimated efficiencies are regressed with demographic and socio-economic variables to identify the factors influencing such efficiency in rice farmers of Indonesia. We used the same set of explanatory variables shown in equation 4 in the second stage regression. The dependent variable in second stage has a censored distribution as it lies between 0 and 1. Therefore, a tobit regression is used to model determinants of technical efficiency. Representing the efficiency score for farm *i* as I_i and *X* be the vector of explanatory variables influencing efficiency, we can present tobit model in the form of following econometric specification defining latent variable framework:

$$I_i = \begin{cases} I_i^* \; if I_i^* > 0 \\ 0 \; otherwise \end{cases} \qquad (7)$$

where I_i is an observed variable, assumed to be related with latent variable I_i^* and $I_i^* = X_i\beta + \vartheta_i$.

Data

Data used in this study comes from a Baseline Survey on Drought-prone environments conducted by International Rice Research Institute (IRRI) in collaboration with Consortium for Unfavorable Rice Environment (CURE) and International Fund for Agricultural Development in

2012. Survey includes 280 households from drought prone areas of West Java, Central Java, and West Nusa Tenggara provinces of Indonesia. We obtained the data from International Rice Research Institute (IRRI)'s website (http://irri.org/tools-and-databases/irri-dataverse, Accessed: August 2015). The baseline study was done to look at the impacts of drought on rice production, assess risk and vulnerability, and determine adaptation strategies of rice farming households. Data contains information about household demographic information, economic status, consumption and income, rice production inputs and outputs as well as gender information on household decision-making.

Table 1 presents definitions and summary statistics of the variables related to rice production, inputs, and household specific information. The total value of rice production in our sample averaged around 147,417 Indonesian Rupiah (IDR). Note that there is a large variation in total rice production as indicated by large standard deviation of 2,176,192. These values are based on farmers' reported farm gate prices and quantities of rice produced. Total value of rice production was up to 3.7 million IRD in some households while the total rice production in kilogram (kg) ranged from 200 kg to 37,000 kg. Farmers in sampled areas have around 1 hectare of rice area per household. The household on average used around 41 kg of rice seed, 213 hours of family labor and 295 hours of hired labor in rice production. Similarly, the household spent around 1,661 on fertilizers & chemicals and 630 in operating bullocks & machinery in rice cultivation.

Table 1 shows that on average a sampled household consists of 4.17 family members with a household head 54 years of age and 5.4 years of formal education; 76% of the household earned some income from off-farm work. On average, 10% of the household faced financial constraint. Standard deviation of 0.30 suggested that there is a wide range in the financial

constraint variable. Note that in our study financial (or credit) constrained households are defined as those households who wanted to borrow but were not able to do so—either they did not have access to credit or faced some other problems in borrowing.

Results and Discussion

We estimated efficiency using both parametric and non-parametric approaches. Table 2 shows the results from stochastic frontier analysis. As a parametric model, we used a Cobb-Douglas production function (described in equation 4) with truncated normal distribution specified for inefficiency term using a maximum likelihood method. The signs of the coefficients of stochastic frontier model are as expected except a non-significant effect of hired labor. Yet labor seems an important component in rice production, hired labor hours were not significant. Family labors, on the other hand, have a significant positive effect. As indicated by a positive elasticity of 0.76, the result suggests that the land as an input has the major influence on rice production. Some previous studies also found the similar effect of land among all other inputs on rice production (Wadud and White 2000). Additionally, fertilizer and chemical cost, which includes costs for pesticides, herbicides, and fertilizers, has a significant positive effect on rice production. Bullocks and machinery used in rice cultivation, on the other hand, has positive and significant but smaller effect. Notice that the variance parameter, gamma is significant and close to one, which indicates that the inefficiency effects are likely to be highly significant in the analysis (Battesse and Coelli, 1995). The significant gamma parameter in particular highlights the importance of examining factors that contribute to inefficiency in rice production.

We also conducted a non-parametric Data Envelopment Analysis (DEA) using the same input and output combinations as shown in equation 4. Note that DEA solves a linear program for every farm separately evaluating them as an individual decision making unit (DMU) and then

presents efficiency associated with every farm. We computed DEA under constant returns to scale (CRS) and variable returns to scale (VRS).

Table 3 shows the summary statistics of the efficiency scores obtained from SFA and DEA. The efficiency scores presented are comparable between two methods. Efficiency results based on SFA suggest that rice farmers in drought prone areas of Indonesia are 72.4% efficient in production, on average. Efficiency based on DEA also suggests similar average results (72.6% efficient under CRS assumption, and 74.2% efficient under VRS assumption). This suggests that there is a scope for improvement in technical efficiency in drought prone areas of Indonesia. The average efficiency score is lower than the previous studies in Indonesia (for eg., Brazdik 2006 found around 77%). A plausible reason is that our sample is from drought prone areas characterized by rainfed cultivation and low input agriculture. Table 3 along with figure 1 shows the skewness and kurtosis of efficiency distribution computed from DEA approach. Note that the skewness is the measure of symmetry (or asymmetry) and kurtosis is the measure of whether the data is peaked or flat relative to normal distribution. A positive skewness (0.78) indicates that the efficiency distribution is little bit skewed to the right (recall normal distribution has skewness=0). Similarly kurtosis (3) indicates the fat tailed distribution of efficiency.

Additionally, table 4 presents the frequency of different level of efficiency. We present the results based on both SFA and DEA approaches. Notice that SFA suggests that 21% of the farms are operating 80-85% efficiently, followed by 75-80% efficient (20%). DEA under CRS, on the other hand suggests 24% of the farms are operating 65-70% efficiently. Nonetheless the overall result suggests that there is a scope for improvement in technical efficiency. It is interesting to investigate about factors influencing such efficiency and find the sources of inefficiency, which we presented in table 5.

The estimated coefficients on the tobit model representing different variables influencing efficiency are particularly interesting in this study. The results from parametric stochastic frontier mode (SFA) and non-parametric Data Envelopment Analysis (DEA) are presented in table 5. The coefficients obtained from both approaches are comparable and have similar sign. Results suggest that household head's age negatively affects technical efficiency. This is consistent with the technology adoption literature, which suggests that older farmers are less recipient and adopter of new technologies and ideas.

Our result on financial variable suggests that the households with financial constraint are less efficient in rice cultivation. As rice cultivation requires some initial investment, or technology adoption and operating costs, financially constraint farmers may not have ability to cope with such requirements which may result them to be less efficient than financially unconstrained farmers. This is further supported by a negative effect of household head's education alone but a positive effect when education is interacted with off-farm work. This indicates that when education is used to bring additional income to the household, it may increase the financial ability of the farmers and thus increases efficiency in production and technology adoption. Moreover our results are consistent with previous studies in Indonesia. Heriqbaldi (2015) found that improving farmer's income and support in financial aspects or providing economic incentives for rice growers in their productive age increases technical efficiency because it reduces farmers' constraint in applying better inputs such as seed, fertilizer, tractor, and machinery in rice farming. Additionally, Brázdik (2006) found that the farmers with credit constraints (having no access to credit) had lower average technical efficiency than those with no credit constraints in some parts of Indonesia, majority of which were characterized by low or no irrigation and infrastructure development.

Conclusion

We estimated technical efficiency of Indonesian rice growers in drought prone areas using a parametric stochastic frontier approach and a non-parametric data envelopment analysis. In addition to the variables used in previous studies, our study also includes the economic and financial variables such as off-farm work participation and financial constraint as the variables in efficiency model. We found that financial constraint negatively influences efficiency while a combine effect of education and off-farm work positively influence efficiency. This result suggest that the policy supporting financial support for farmers or engaging them in short- or long- term income generation activities may help to increase efficiency in rice farmers across drought prone areas of Indonesia.

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Table 1: Descriptive statistics

Variable	Description	Mean	Standard Deviation
Rice Production	Value of total rice production in the household	147,417.40	2,176,192
Land	Total land cultivated under rice (in ha)	1.07	1.13
Family Labor	Total family labor hours used in rice production	213.25	340.46
Hired Labor	Total hired labor hours used in rice production	294.51	633.28
Seed	Amount of seed used (in kg)	41.11	30.87
Fertilizer & chemicals cost	Total costs of fertilizers, chemicals, and pesticides used	1660.70	2602.86
Bullocks & Machinery cost	Total cost of bullocks, tractors, and machinery used in rice cultivation	630.31	717.87
Age	Age of the household head (in years)	54.38	11.43
Education	Years of education of household head	5.41	2.88
Family size	Number of family members in the household	4.17	1.83
Off-farm work	(=1 if the household received off-farm income from off-farm works, else 0)	0.76	0.43
Credit constraint	Dummy variable (=1 if the household faced problem in borrowing money or had not an access though the household wanted to borrow; 0 else)	0.10	0.30
Number of Observations		278	

Table 2: Stochastic Frontier Analysis

Variables	Coefficient	T-statistics
Constant	7.912**	(4.20)
Log Land	0.759**	(13.44)
Log hired labor	-0.0239	(-0.82)
Log family labor	0.0484**	(2.22)
Log seed	0.0222	(0.42)
Log fertilizer and chemicals	0.237**	(4.40)
Log bullocks and machinery	0.0245*	(1.68)
σ_u^2	1.003	
σ_v^2	0.243	
Gamma	0.990**	
Log likelihood	-203.54	
N	243	

Dependent variable: total value of rice produced; t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$

Table 3: Summary of efficiency scores

Method	Mean efficiency score	Std. Dev.	Skewness	Kurtosis
Stochastic Frontier Analysis	0.724	0.141		
Data Envelopment Analysis				
CRS	0.726	0.098	0.788	3.447
VRS	0.742	0.102	0.770	3.216

Table 4: Efficiency scores and frequency

Efficiency Score	Stochastic Frontier model (SFA)		Data Envelopment Analysis (DEA)			
			CRS		VRS	
	No. of farms	% of farms	No. of farms	% of farms	No. of farms	% of farms
<50%	19	7	0	0	0	0
50-55	4	1	3	1	2	1
55-60	12	4	15	5	11	4
60-65	15	5	45	16	39	14
65-70	21	8	67	24	57	21
70-75	35	13	51	18	60	22
75-80	55	20	45	16	41	15
80-85	57	21	20	7	28	10
85-90	29	10	17	6	15	5
90-95	20	7	6	2	12	4
95-100	15	5	4	1	2	1

Table 5: Factors influencing efficiency

Variables	SFA		DEA			
			CRS		VRS	
	Coefficient	Standard Error	Coefficient	Standard error	Coefficient	Standard error
Constant	0.878**	0.108	0.941**	0. 081	0.977**	0.084
Family Size	0.005	0.006	-0.002	0.005	-0.001	0.005
Age, household head	-0.001**	0.000	-0.002**	0.001	-0.003**	0.001
Education, household head	-0.043**	0.009	-0.016**	0.006	-0.017**	0.006
Off-farm income	-0.216**	0.050	-0.051	0.040	-0.063	0.043
Financial constraint	-0.049**	0.017	-0.031**	0.011	-0.032**	0.006
Education X off-farm income	0.049**	0.009	0.011**	0.007	0.013**	0.007

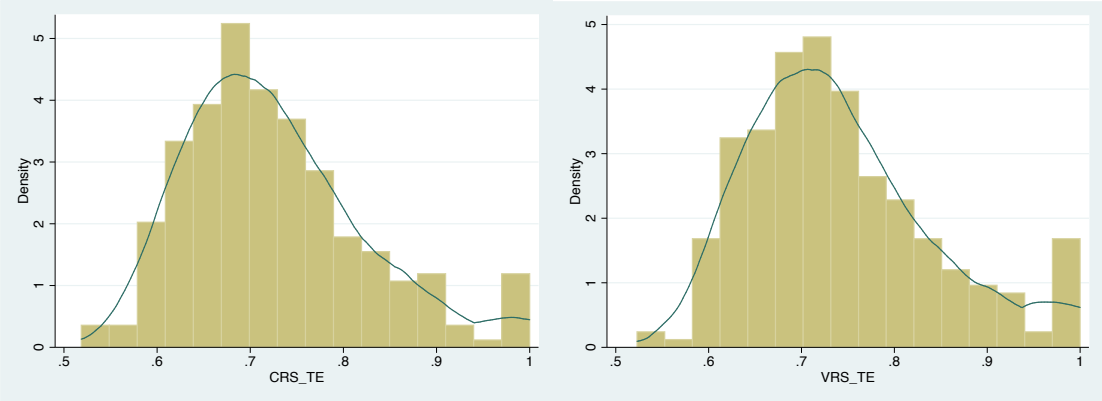

Figure 1: Distribution of efficiency scores [predicted from DEA frontier estimation: under constant returns to scale assumption (left) and variable returns to scale assumption (right)]