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Adoption of rice cultivation technologies and its effect on technical efficiency in Sagnarigu District of Ghana

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Abstract: This study examined the adoption of rice cultivation technologies on farmers' technical efficiency in Sagnarigu District. The stochastic frontier model was used to estimate the determinants of output and technical inefficiency while propensity score matching was also used to analyse the average treatment effect (ATE) and the average treatment effect on the treated (ATT). A total of 120 respondents comprising 60 adopters and 60 non-adopters were randomly selected from six communities in the District and interviewed using semi-structured questionnaires. Farm size, fertilizer, weedicides and household labour had positive and significant effect on rice output. Farmers who adopted the rice cultivation techniques were less technically inefficient than those who did not adopt. The ATT was 0.121 which implies that farmers who adopted the rice technologies increased their technical efficiency by about 12% and this was significant at 10% for the PSM with similar results obtained for the nearest neighbour matching. The ATE value of 0.102 which was also statistically significant at 10% means that farmers on the whole increased their

Shamsudeen Abdulai

ABOUT THE AUTHOR

My involvement in research over the past seven years have been in the areas (My co-authors have similar research interests and we have been collaborating for many years now) of crop and farmer productivity improvement, technology dissemination and adoption, food security, project evaluation and impact assessment, income and welfare analysis as well as rural development in Northern Ghana. My field practical and research experience have led to the publication of five scientific peer-reviewed research papers. My co-authors have similar research interests and we have been collaborating for many years now. Additionally, I supervised a baseline survey for an on-going Innovation Laboratory for Small Scale Irrigation Project in Northern Ghana for the International Food Policy Research Institute with University for Development Studies as research partner in 2015. I was also a member of a Research Team (2011–2013) responsible for data collection, analysis and writing baseline report and end of programme assessment of a United Nations Human Security Programme in Northern Ghana with University for Development Studies as research partner.

PUBLIC INTEREST STATEMENT

Ghana spends USD 600 m annually importing 70% of domestic rice requirement to fill the deficit in supply. This study examined adoption of rice cultivation practices (bund construction, harrowing, farrowing, drilling, plant spacing, fertilizer application and planting Jasmine 85 seed) on 60 adopter and 60 non-adopter rice farmers' technical efficiency in Sagnarigu District. Technical efficiency is obtaining maximum rice output from a set of farm inputs.

Farm size, fertilizer, weedicides and household labour had positive effect on rice output. Mean technical efficiency estimates for adopters and non-adopters were 58% and 48% emphasizing the significance of adoption on farmers' output. Nonetheless, additional mean output of 42% could be realized by adopters if they operated under full efficiency and adopted the cultivation practices to the letter. This study recommends more rice farmers be encouraged to adopt the cultivation practices in order to improve their output levels.

technical efficiency by 10.2%. Moreover, the mean technical efficiency estimates for adopters and non-adopters were about 58% and 48% respectively under regression adjustment and inverse-probability weights. The existence of a technical efficiency gap of 10% between adopters and non-adopters of rice technologies emphasized the significant effect of technology adoption on farmer's technical efficiency. The study recommends that more rice farmers should be encouraged to adopt the rice production technologies in order to improve their technical efficiency levels.

Subjects: Environment & Agriculture; Food Science & Technology; Development Studies, Environment, Social Work, Urban Studies; Social Sciences; Development Studies; Economics, Finance, Business & Industry

Keywords: adoption; propensity score matching; technical efficiency; treatment effects; Sagnarigu District; Ghana

1. Introduction

Rice is a global staple providing nutrition and calories for more than half of the world's population (Akighir & Shabu, 2011; Nwanze, Mohapatra, Kormawa, Shellemiah, & Bruce-Oliver, 2006; Zhou, Robards, Helliwell, & Blanchard, 2002). The Green Revolution led to the adoption of improved agricultural production techniques and made Asia largely self-sufficient in rice production (Huy, 2007). This means that productivity improvement in rice production is possible through adoption of improved agricultural techniques.

According to Nwanze et al. (2006), about 20 million farmers in SSA grow rice while about 100 million people depend on it for their livelihoods. Between 2007 and 2010, domestic paddy production in SSA grew by 14% (CARD, 2013). Nonetheless, in Africa, domestic production still remains lower than the demand for the rice. For instance, Ghana currently imports more than 70% of its domestic rice requirement at a cost of about USD 600 million per annum (MoFEP, 2009) to make up for the deficit in rice supply. This import bill drains large amounts of scarce foreign exchange (Nutsugah et al., 2011; Ragasa et al., 2013). Narrowing the gap between domestic demand and production would require implementation of measures to not only expand the area under cultivation, but also, increase rice yields by at least 50% (Aker, Block, Ramachandran, & Timmer, 2011; Olaf & Emmanuel, 2009). According to Asante, Wiredu, and Martey (2014), rice production has become a focal point for policy makers, NGOs and other stakeholders because of the rapidly increasing human population and the need for sustainable food security. According to Ragasa et al. (2013), the leading domestic rice producing regions in Ghana are the Northern (37%), Upper East (27%), and Volta Regions (15%).

Against this backdrop, farm resources need to be used more efficiently in order to reduce waste and increase output. According to Alhassan (2008), technical efficiency is a key factor for productivity growth. Technical efficiency measures the extent to which output can be raised without increasing input use under a given production technology.

The Northern Region of Ghana has good potential for rice production and for this reason, the Japan International Cooperation Agency (JICA) in collaboration with Ministry of Food and Agriculture (MoFA) in 2009, introduced new rice production technologies under its project "Sustainable Development of Rain-fed Lowland Rice". These new rice production technologies were bund construction, harrowing, farrowing, drilling, plant spacing (20*30 cm), seed selection by soaking, fertilizer application (NPK-80 kg/ha and Nitrogen Sulphate 50 kg/ha) and use of Gbewa rice (Jasmine 85) seed. This study therefore seeks to assess the effect of adoption of these technologies on farmers' technical efficiency.

2. Material and methods

2.1. Study area and sampling approach

The study area is Sagnarigu District in Northern Region of Ghana. The district has an estimated total land size of 114.29 square kilometres (representing 26% of the total landmass of the region). Twenty (20) respondents, comprising 10 JICA and 10 non-JICA rice farmers were randomly sampled in each community and information collected relative to the 2012/2013 cropping season using semi-structured questionnaires. The total sample size was 120 respondents from six communities in the district.

2.2. The poisson model

Adoption studies mostly employ a probit/logit model to determine the factors that influence the adoption of where only one new technology is involved. However, where there is adoption of more than one technology, the Poisson model is most appropriate. Ordinary least squares (OLS) estimation is not suitable because, the basic assumptions of normality and homoscedasticity of the error term would be violated and more so, the computed probabilities may lie outside the 0–1 range (Greene, 2003). In binary models, the regressand, (adoption) is unobservable, a dummy variable which indicates whether a farmer adopts or does not adopt a given technology is what is observed. A farmer's decision to fully practice a technology depends on a utility index (I_i), which is determined by one or more explanatory variables such as education, in such a way that, the larger the value of the utility index, the greater the probability of a farmer adopting the technology and vice versa. Nonetheless, a binary model fails to account for the number of technologies adopted per farmer.

The number of rice production technologies adopted is an integer such as 0, 1, 2 … 8. This means a Poisson model is more appropriate than standard linear regression, which yields parameter estimates that are inefficient, biased, and or unacceptable predicted values (Greene, 1997; King, 1988). According to Greene (1997), the Poisson regression is represented by the basic equation:

$$\Pr(Y = y) = \frac{e^{-\lambda}\lambda^{y}}{y!} \qquad y = 0, 1, 2, 3 \ldots .. \tag{1}$$

The parameter λ is assumed to be log-linearly related to the independent variable, (X_i) and dependent variable, (Y). A Poisson random variable with its probability density function is given as.

$$f(Y_i/Xi) = \frac{\mu^{Y}e^{-\mu}}{Y!} Y = 0, 1, 2 \ldots \tag{2}$$

where f (Y) denotes the probability that the variable Y takes non-negative integer values, and $Y!$ stands for = $Y \times (Y-1) \times (Y-2) \times 2 \times 1$. Since its variance is equal to the mean value, the Poisson regression model can be written as:

$$Y_i = E(Y_i) + u_i = \mu_i + u_i \tag{3}$$

For estimation purposes, the parameter μ_i which takes a log linear functional form is used:

$$\ln(\lambda) = \beta' X, \tag{4}$$

The log-likelihood function is given by the equation:

$$\ln L = \Sigma_{i=1,2\ldots\ldots n}[-\lambda_i + y_i + \beta' x_i - lny_i!] \tag{5}$$

Therefore, the adoption model is given as:

$$A = \beta_0 + \beta_i X_i + u_i \tag{6}$$

where A is dependent variable (adoption); β_0 is the intercept; β_i are the coefficients of the explanatory variables; X_i are the explanatory variables and u_i is the error term.

The empirical model for adoption is specified as

$$A_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 C + \beta_3 X_3 + \beta_4 X_4 + u_i \quad (7)$$

where X_1 is farm size in hectares; X_2 is access to contract rice farming; X_3 is access to agricultural extension service; X_4 is farmer group membership.

2.3. Stochastic frontier model

This model was independently proposed by Aigner, Lovell, and Schmidt (1977); Meeusen and Broeck (1977) and expanded by Jondrow, Lovelle, Materov, and Schmidt (1982). According to Farrell (1957), efficiency is decomposed into technical (TE) and allocative (AE) and their combination gives economic efficiency (EE). Thus, EE = TE*AE. A firm is allocatively efficient when production occurs at a point where the marginal value product is equal to the marginal factor cost. Technical efficiency is the ability to obtain maximum output from a set of inputs under a given production technology. Therefore, an efficient firm produces on its production possibility frontier. The stochastic frontier model is represented as:

$$Y_i = X_i;\beta + \varepsilon_i \quad (8)$$

where Y_i is output of the *i*th farm, $(X_i; \beta)$ is a suitable functional form such as the Cobb-Douglas or the translog of a *1 x k* vector of farm inputs and a *k x 1* vector of parameters to be estimated, ε is the composed error term which is equal to *v* + *u*. Technical efficiency is given by:

$$TE = \frac{Y_i}{Y_i^*} = \frac{f(X_i,\beta)\exp(V_i - U_i)}{f(X_i,\beta)\exp V_i} = \exp(-U_i) \quad (9)$$

where Y_i is the observed output and Y_i^* is the highest predicted value of the frontier output. The study also adapts the model proposed by Battese and Coelli (1995), who expressed technical inefficiency, TI effects by:

$$U_i = Z_i\delta + w_i \quad (10)$$

where Z_i is a $(1 \times m)$ vector of explanatory variables associated with the TI effects; δ is a $(m \times 1)$ vector of unknown parameters to be estimated; and w_i is an unobservable random variable. The parameters indicate the impacts of variables in *Z* on *TE*. A negative value suggests a positive influence on *TE* and vice versa.

2.4. Impact of adoption on technical efficiency

The Propensity Score Matching (PSM) technique, first proposed by Rosenbaum and Rubin (1983), is used by researchers to evaluate the effect of a programme intervention. In this study, PSM is used to construct a group for comparisons based on probability model of adoption of JICA rice cultivation technologies. This approach corrects for sample selectivity bias in programme interventions, since the selection of participants are often non-random (Diagne & Demont, 2007; Imbens & Wooldridge, 2009). The PSM helps in comparing the technical efficiency of technology adopters to that of the counterfactual non-adopters according to the predicted propensity of adopting at least one technology (Asante et al., 2014; Caliendo & Kopeinig, 2008; Heckman, Ichimura, Smith, & Todd, 1998; Rosenbaum & Rubin, 1983; Smith & Todd, 2005; Wooldridge, 2005).

The PSM also allows for examination of the probability of adoption in addition to assessing the effect of adoption on technical efficiency. The average treatment effect (ATE) is estimated as the

mean difference in technical efficiency between adopters, denoted by Y(1) and matched control group, denoted by Y(0).

$$\text{ATE} = \text{E}\left[\text{Y}(1) - \text{Y}(0)\right] = \text{E}\left[\text{Y}(1)\right] - \text{E}\left[\text{Y}(0)\right] \tag{11}$$

The ATE compares the technical efficiency of farmers who adopted one or more technologies with that of non-adopters or control farmers that are similar in terms of observable characteristics and also partially control for non-random selection of participants in the JICA rice cultivation technology adoption programme.

The average treatment effect on the treated (ATT), measures the effect of adoption on the technical efficiency of farmers who actually adopted only the JICA rice technologies rather than across all rice farmers who potentially could have adopted these technologies. ATT is calculated as follows:

$$\text{ATT} = \text{E}\left[\text{Y}(1) - \text{Y}(0)|\text{G} = 1\right] = \text{E}\left[\text{Y}(1)|\text{G} = 1\right] - \text{E}\left[\text{Y}(0)|\text{G} = 1\right] \tag{12}$$

It is also possible to estimate the average treatment effect on the untreated or control groups (ATC), which measures what the effect of adoption on technical efficiency would be for farmers who did not actually adopt the JICA rice technology. ATC is expressed by:

$$\text{ATC} = \text{E}\left[\text{Y}(1) - \text{Y}(0)|\text{G} = 0\right] = \text{E}\left[\text{Y}(1)|\text{G} = 0\right] - \text{E}\left[\text{Y}(0)|\text{G} = 0\right] \tag{13}$$

2.5. Empirical model of stochastic frontier

The generalized likelihood ratio test is used to ascertain the appropriateness of the use of either the Cobb-Douglas or the translog functional form and also to determine the relationship between rice output and the socioeconomic, institutional and farm-specific factors. The generalized likelihood-ratio test is of the form:

$$k = -2\left[\ln\left\{L\left(H_A\right)\right\}/\ln\left\{L\left(H_0\right)\right\}\right] = -2\left[\ln\left\{L\left(H_A\right)\right\} - \ln\left\{L\left(H_0\right)\right\}\right] \tag{14}$$

where $L(H_A)$ and $L(H_0)$ are the values of the likelihood function under the alternative and null hypotheses. The value of k has a Chi-square, $\chi 2$ (or mixed chi-square) distribution with the number of degrees of freedom equal to the difference between the number of parameters involved in H_0 and H_A.

The Cobb-Douglas functional form is specified as follows:

$$\ln Y = \beta_0 + \ln\beta_1 X_1 + \ln\beta_2 X_2 + \ln\beta_3 X_3 + \ln\beta_4 X_4 + \ln\beta_5 X_5 + V_i - U_i \tag{15}$$

Also, the translog model is represented by:

$$\ln = \beta_0 \sum_{K=1}^{5} \beta_k \ln X_{ik} + \frac{1}{2}\sum_{k=1}^{5}\sum_{j=1}^{5} \beta_{kj} \ln X_{ik} \ln X_{ij} + V_i + U_i \tag{16}$$

where Y is rice output (kg), X_1 is household labour, X_2 is seed quantity used (kg), X_3 is weedicides quantity (litres), X_4 is fertilizer used (kg), X_5 is farm size (ha).

Technical inefficiency is expressed as:

$$TE_i = \delta_0 + \delta_1 K_1 + \delta_2 K_2 + \delta_3 K_3 + \delta_4 K_4 + \delta_5 K_5 + \delta_6 A_6 + e_i \tag{17}$$

where K_1 is education (in years), K_2 is sex (dummy 1 = male, 0 = female), K_3 is access to credit (dummy 1 = access, 0 = no access), K_4 is access to fertilizer subsidy (dummy 1 = access, 0 = no access), K_5 is access to agricultural extension (dummy 1 = access, 0 = no access), and A_6 is predicted values of adoption.

3. Results and discussion

3.1. Definition and descriptive statistics of variables

Table 1 contains the descriptive statistics of variables in the study area. The results show the mean age of rice farmers was about 33 years. This implies a relatively youthful farmer population and with adequate motivation, they can help raise rice yield.

The mean of 1.5 years of formal education is indicative of low level of formal education and the fact that most rice farmers could not even make it past basic two. On average, a household had a farm size of about a hectare for rice cultivation with three household members providing labour on this plot. The mean yield of rice was 3.44 mt/ha in the study area compared with the national achievable yield of 6.5 mt/ha (MoFA, 2011), hence the need to bridge this yield gap by adopting improved cultivation practices and combining the right input mix. The mean quantity of rice seed planted was 8.2, 411.5 kg/ha for fertilizer and 3.1 litres/ha for weedicides as presented in Table 1.

3.2. Determinants of adoption of rice cultivation technologies

The results of the determinants of adoption as shown in Table 2 indicate that contract farming, farmer' group association and access to agricultural extension had positive and significant effect on adoption of rice cultivation technologies.

First and foremost, contract farming was significant at 1% and had a positive effect on adoption. This means that rice farmers contracted to produce for a ready market adopted more of the rice production technologies than their counterparts who were not into contract farming. Contract farming provides a ready market incentive for rice farmers to want to produce more by adopting improved cultivation technologies.

Secondly, group membership had a positive influence on adoption and was statistically significant at 1%. This implies that, farmers who belonged to a farmer group had greater probability of adopting more rice cultivation techniques which is in line with Abdallah et al. (2014), that group membership had positive influence on adoption. Nonetheless, Martey et al. (2013) found a negative influence of group membership on adoption. Group membership provides among other things, positive peer influence and opportunity to learn good practices from friends.

Table 1. Descriptive statistics of variables

Variable description	Mean	Min	Max
Age (in years)	33.35	18	64
Fertilizer use (in kilogrammes)	411.4	50	1,235
Rice output (in kilogrammes)	3,440.5	100	16,302
Education (No. of years in school)	1.5	0.0	12
Farm size (in hectares)	1.0	0.5	4
Household labour (No. of persons)	2.9	1.0	16
Contract farming (dummy, 1 = yes, 0, otherwise)	0.43	0.0	1
Seed used (in kilogrammes)	8.2	0.5	40
Weedicides used (in litres)	3.1	0.0	15
Agricultural extension (dummy, 1 = access, 0, otherwise)	0.7	0.0	1
Training in rice cultivation (dummy, 1 =access, 0, otherwise)	0.7	0.0	1
Farmer group association (dummy, 1 = yes, 0, otherwise)	0.6	0.0	1
Fertilizer subsidy (dummy, 1=access, 0, otherwise)	0.5	0.0	1
Credit dummy, 1= access, 0, otherwise)	0.1	0.0	1
Gender (dummy, 1 =male, 0, female)	0.7	0.0	1

Source: Authors' Computation, 2017.

Table 2. Maximum likelihood estimates of the poisson model

Variable	Coefficient	Standard error	*p*-value
Constant	0.244	0.1681	0.147
Contract farming	0.636***	0.119	0.000
Farmers group	0.421***	0.145	0.004
Farm size	−0.004	0.079	0.955
Access to agric. extension	0.674***	0.178	0.000

Source: Authors' Computation, 2017.

***Means statistically significant at 1%.

Thirdly, there was a positive relationship (significant at 1%) between access to agricultural extension service and adoption of rice production technologies. This implies that farmers who had access to agricultural extension service adopted more of the production technologies than those who did not have access. Agricultural extension is the means by which information on improved and new production technologies are disseminated to farmers. It contributes to reduction of productivity differential by increasing the speed of technology transfer (Abdulai, 2015). This is consistent with the findings of Donkoh and Awuni (2011), Ransom, Paudyal, and Adhikari (2003) and Doss and Morris (2001), but contrary to Abdallah et al. (2013), who reported a negative influence of agricultural extension on adoption.

3.3. Test of hypotheses

The generalized likelihood ratio test found the translog functional form appropriate for the stochastic frontier analysis (see Table 3). The null hypothesis that the socioeconomic variables did not explain the presence of technical inefficiency was also rejected in this study.

3.4. Determinants of rice output

The results of Maximum Likelihood (ML) estimates of the stochastic frontier for rice production are shown in Table 4. The output and input variables were normalized against their respective mean values and therefore the first term variables could be interpreted as elasticities of output relative to the inputs (Abdulai, 2015; Kuwornu, Amoah, & Seini, 2013). The first term factor variables with the exception of seed had positive and significant effect on rice output. For example, the coefficient of seed was -0.058 and statistically significant 1%. This means that when quantity of seed sowed increases by 100%, holding all other variable inputs constant, output would decrease by about 5.8%, bringing to the fore the need to stay within optimum plant density. Notwithstanding, household labour, weedicides, fertilizer and farm size had positive production elasticities of 0.269, 0.517, 0.235 and 0.228 respectively. This means that when each of these inputs such as weedicides, fertilizer and farm size is increased by 100%, rice output would increase by 51.7, 23.5 and 22.8% respectively, other things being equal. The variable input with the highest partial elasticity (0.517) was weedicides. Weeds compete with crop plants for nutrients and water among others, hence, weedicides are

Table 3. Test for choice of functional form and presence of inefficiency

Test	Null hypothesis	Log likelihood function (H_0)	Test statistic λ	Critical value	Decision
Choice of functional form	H_0:$\beta_1 = \ldots = \beta_{20} = 0$	−143.703	32.119	12.592 (15)	Reject H_0: Translog appropriate
Presence of inefficiency term	H_0:$\delta_1 = \cdots = \delta_6 = 0$	−110.3105	30.369	24.996(6)	Reject H_0

Notes: Critical values are at 5% significance level and obtained from χ^2 distribution table. Figures in brackets are the number of restrictions.

Table 4. Maximum likelihood estimates of the translog and inefficiency models

Variable	Coefficient	Standard error	*p*-value
Constant	8.330	0.00188	0.000
Household labour	0.269***	0.0217	0.000
Seed	−0.058***	0.00736	0.000
Weedicides	0.517***	0.00713	0.000
Fertilizer	0.235**	0.0846	0.005
Farm size	0.228***	0.0535	0.000
Household labour squared	−3.005***	0.755	0.000
Seed squared	−0.267***	0.00318	0.000
Weedicides squared	0.227	0.209	0.278
Fertilizer squared	−0.067	0.050	0.183
Farm size squared	−0.847**	0.518	0.102
Household labour*Seed	0.102***	0.0182	0.000
Household labour*Weedicides	−0.325**	0.131	0.013
Household labour*Fertilizer	−0.372***	0.089	0.000
Household labour*Farm size	0.797***	0.204	0.000
Seed*Weedicides	0.199**	0.064	0.002
Seed*Fertilizer	0.081***	0.0162	0.000
Seed*Farm size	−0.172**	0.069	0.013
Weedicides*Fertilizer	0.617**	0.369	0.094
Weedicide*Farm size	−0.645***	0.099	0.000
Fertilizer*Farm size	0.109	0.389	0.779
Inefficiency term			
Constant	−1.403	0.395	0.000
Gender	0.392	0.324	0.227
Access to credit	1.689***	0.451	0.000
Access to agric. extension	1.622***	0.448	0.000
Predicted value adoption	−0.558***	0.130	0.000
Sigma square	−33.612*	122.426	0.061
Gamma	0.274***	0.022	0.000
Returns to scale	1.191		
Log likelihood	110.311		

Source: Authors' Computation, 2017.

*Means statistically significant at 10%.

**Means statistically significant at 5%.

***Means statistically significant at 1%.

increasingly being substituted for other methods of weeds control during land preparation and immediately after sowing (Abdulai, 2015).

Additionally, the squared values of household labour, seed, weedicides and farm size were statistically significant and had negative signs which means that their continuous use in the long run would lead to a reduction in rice output.

The interaction terms of the factor variables explain whether the production inputs are substitutes or complements in rice production. For example, "household labour and seed"; "household labour and farm size"; "seed and weedicide"; "seed and fertilizer"; and "weedicide and fertilizer" had

positive coefficients and statistically significant and thus were complements to each other in rice production. Nonetheless, the interaction terms of factor variables such as "household labour and weedicide", "household labour and fertilizer"; "seed and farm size" as well as "weedicide and farm size" had negative coefficients and therefore were substitutes to each other in rice production.

The sigma squared value of 33.612 was significantly different from zero at 1% significance level and indicated the correctness of the specified distributional assumption for the inefficiency term, U_i. The returns to scale value of 1.191 indicated increasing returns to scale. This means that rice production in Sagnarigu District was in stage one of the production function and thus inputs were being under-used. Therefore, an increase in the use of the variable inputs in the production process would lead to a more than proportionate increase in output.

3.5. Determinants of technical inefficiency

The determinants of inefficiency are explained using the estimated (δ) coefficients associated with the inefficiency effects in Table 4. The socio-economic variables with negative coefficients have positive relationships with inefficiency and vice versa. The determinants of technical inefficiency were access to production credit, agricultural extension and the adoption of rice production technologies. To begin with, access to production credit had positive effect on inefficiency and statistically significant at 1%. Many of the farmers in the study area did not have access to formal credit to assist them in rice production. A handful of farmers had woefully inadequate credit amount which even had negative effect on their technical efficiency.

Nonetheless, access to agricultural extension had positive coefficient and statistically significant in the study. However, Figure 1 shows that farmers who had access to agricultural extension service in rice production were much better than those who did not have access to agricultural extension in terms of technical efficiency with a standard error of 0.06.

Last but not least, the predicted value of adoption had negative coefficient and statistically significant at 5%. This means that rice farmers who adopted the rice production technologies were more technically efficient (or less technically inefficient) than those who did not adopt with standard error of 0.07 as presented in Figure 2.

3.6. Distribution of technical efficiency scores

The estimated technical efficiencies for smallholder rice farmers ranged from 0.074 to 99% with a mean of 54%. This means there is a huge potential to increase rice output up to 46% without increasing the existing level of factor inputs. Additionally, about 40% of rice farmers had technical efficiency scores above 0.60 while 50% of respondents had scores of 0.50 or less. The mean technical efficiency found in the study area was low, compared with for instance Alhassan (2008) who found mean technical efficiencies of 51 and 53% for irrigated and non-irrigated rice production in northern Ghana as well as Abdulai and Huffman (2000) who had a mean technical efficiency of 81% for rice farmers in northern Ghana with 19% of potential output lost to inefficiency.

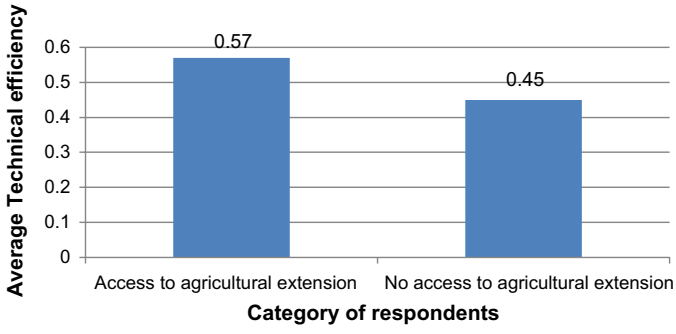

Figure 1. Average efficiency and access to agricultural extension.

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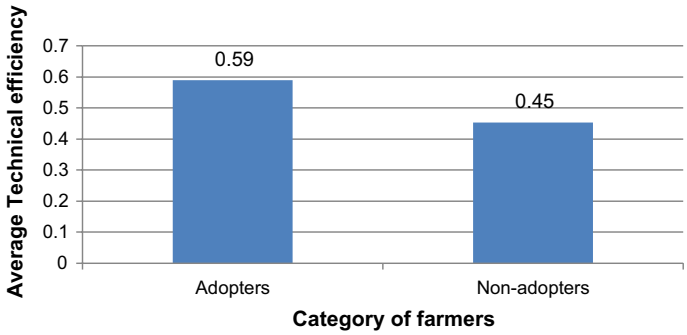

Figure 2. Average efficiency and adoption of rice production technologies.

Table 5. Technical efficiency scores

Efficiency range	Adopters		Non-adopters		Pooled Data	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
≤ 0.50	23	38.33	37	61.67	60	50
0.51–0.60	6	10	6	10	12	10
0.61–0.70	7	11.67	4	6.67	11	9.17
0.71–0.80	5	8.33	3	5	8	6.67
0.81–0.90	3	5	3	5	6	5
0.91–1.00	16	26.67	7	11.67	23	19.17
Total	60	100	60	100	120	100
Mean TE	0.62		0.46		0.54	
Min.	0.0007		0.008		0.00074	
Max.	1.00		1.00		0.99	
Standard deviation	0.298		0.293		0.31	

Source: Authors' Computation, 2017.

The mean technical efficiency estimates for adopters and non-adopters were 0.62 and 0.46 respectively. The overall mean technical efficiency for rice farmers in the study area was 0.54 with standard deviation of 0.31 (see Table 5). At above 0.60 technical efficiency score, the adopters had high technical efficiency (51.7%) compared with their non-adopter counterparts (28.4%).

3.7. Impact of adoption of rice technologies on farmers' technical efficiency

The stochastic frontier model was used to estimate the determinants of output and technical inefficiency while propensity score matching was also used to analyse the average treatment effect (ATE) and the average treatment effect on the treated (ATT) of adoption on technical efficiency as contained in Table 6. The ATT value was 0.121 which implies that farmers who adopted the JICA rice cultivation technologies increased their technical efficiency by about 12% and this was significant at 10% for the PSM with similar results obtained for the nearest neighbour matching (NNM). The ATE value of 0.102 which was also statistically significant at 10% means that farmers on the whole increased their technical efficiency by 10.2%. Moreover, the mean technical efficiency estimates for adopters and non-adopters were about 58 and 48% respectively under regression adjustment and inverse-probability weights.

The fact that there exist a technical efficiency gap of 10% between adopters and non-adopters of rice technologies, gives credence to the significant effect of technology adoption on farmer's technical efficiency, thus the need to intensify efforts to encourage adoption of improved rice production technologies. Rice farmers who adopted the rice production technologies were more technically efficient.

Table 6. Results of effect of adoption of cultivation technologies on rice output

	Propensity score matching (PSM)		Nearest neighbor matching (NNM)		Regression adjustment[a]	
	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
ATE	0.101*	0.061	0.101**	0.060		
ATT	0.121*	0.720	0.121**	0.731		
Mean efficiency adopters					0.584***	0.039
Mean efficiency non-adopters					0.479***	0.053

Source: Authors' Computation, 2017.

*Indicate statistical significance at 10%.

**Indicate statistical significance at 5%.

***Indicate statistical significance at 1%.

[a]Similar results obtained using inverse probability weights.

3.8. Conclusions and recommendations

This study employed PSM to assess the effect of adoption of JICA rice cultivation technologies on farmers' technical efficiency in the Sagnarigu District of Ghana. Contract farming, farmer' group membership and access to agricultural extension service had positive and significant effect on adoption. Rice farmers who had contracts with buyers adopted more of the rice production technologies due to the ready market incentive than their counterparts who were not into contract farming. Farmers who belonged to farmer groups also had greater adoption than those who did not. The agricultural extension service of the Ministry of Food and Agriculture should be strengthened and easily accessible to rice farmers seeking cultivation advice to enable them improve on their rice yield. Similarly, household labour, use of weedicides, fertilizer and farm size had positive and significant effect on rice output.

The mean technical efficiency estimates for adopters and non-adopters were 0.58 and 0.48 respectively. A technical efficiency gap of 0.1 between adopters and non-adopters of rice technologies relative to the PSM was indicative of the significant effect of technology adoption on farmer's technical efficiency. The study recommends that more rice farmers should be encouraged to adopt the rice production technologies in order to improve their technical efficiency levels and consequently improve yield.

Abbreviations

AE	Allocative efficiency
CARD	Centre for Agricultural and Rural Development
EE	Economic Efficiency
JICA	Japan International Cooperation Agency
MoFA	Ministry of Food and Agriculture
MoFEP	Ministry of Finance and Economic Planning
NGOs	Non-Governmental Organizations
NNM	Nearest Neighbour Matching
PSM	Propensity Score Matching
TE	Technical Efficiency
TI	Technical Inefficiency
SSA	sub-Saharan Africa
SFA	Stochastic Frontier Approach

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Competing interests
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Cover image
Source: Jinbaani, N. & Authors, 2017. Photograph taken from rice field in Northern Ghana with farmer's permission.

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