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Agricultural microcredit and technical efficiency: The case of smallholder rice farmers in Northern Ghana

Benjamin Tetteh Anang [a,b,*], Stefan Bäckman [a], Timo Sipiläinen [a]

[a]Department of Economics and Management, University of Helsinki, FI-00014, Finland
[b]Department of Agricultural and Resource Economics, Faculty of Agribusiness and Communication Sciences, University for Development Studies, Tamale, Ghana

Abstract

In the current study, we compared technical efficiency of smallholder rice farmers with and without credit in northern Ghana using data from a farm household survey. We fitted a stochastic frontier production function to input and output data to measure technical efficiency. We addressed self-selection into credit participation using propensity score matching and found that the mean efficiency did not differ between credit users and non-users. Credit-participating households had an efficiency of 63.0 percent compared to 61.7 percent for non-participants. The results indicate significant inefficiencies in production and thus a high scope for improving farmers' technical efficiency through better use of available resources at the current level of technology. Apart from labour and capital, all the conventional farm inputs had a significant effect on rice production. The determinants of efficiency included the respondent's age, sex, educational status, distance to the nearest market, herd ownership, access to irrigation and specialisation in rice production. From a policy perspective, we recommend that the credit should be channelled to farmers who demonstrate the need for it and show the commitment to improve their production through external financing. Such a screening mechanism will ensure that the credit goes to the right farmers who need it to improve their technical efficiency.

Keywords: microcredit, propensity score matching, selection bias, smallholder farming, stochastic frontier analysis, technical efficiency

1 Introduction

Majority of Ghanaian smallholder farmers operate less than 2 hectares of land (Seini & Nyanteng, 2005). As a result of limited use of capital and low adoption of production technologies, yields and incomes among smallholders are generally low. The participation of Ghanaian smallholders in the formal financial sector is limited by lack of collateral, perceived high risk of lending, and high transaction cost of loans (Boniphace *et al.*, 2015; UNCTAD, 2015) while statistics attest the fact that the demand for financial services for rural people remains largely unmet (Zeller & Sharma, 1998; UNDP, 2004). Commercial banks are not interested in lending to rural households due to lack of individual collateral (Phillip *et al.*, 2008). According to Anang *et al.* (2015), some lenders may consider farm households without adequate capital endowment too poor and not creditworthy thus limiting their access to credit. Dittoh (2006) identified access to credit as the main concern of Ghanaian small-scale farmers. According to some researchers, the lack of access to credit (and other financial services) by smallholder farmers has implications for agricultural development, farm efficiency and productivity (Owusu-Antwi, 2010; Boniphace *et al.*, 2015). Liquidity constraints therefore impact agricultural growth and productivity in northern Ghana.

* Corresponding author
Email: benjamin.anang@helsinki.fi

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Credit is a key component of financial services and fundamental in all aspects of production, including agricultural production. Agricultural production and financial decisions by farm households are interrelated and this has led to a growing research interest in order to understand this interrelationship (Barry & Robinson, 2001). A large body of literature highlights the important role of credit in agricultural production (Chaovanapoonphol *et al.*, 2005; Ruben & Kolk, 2005; Dittoh, 2006; Komicha & Öhlmer, 2007; Martey *et al.*, 2015). These studies portray the key role of agricultural credit in technical efficiency and productivity of farm households. The role of credit in raising both the technical and allocative efficiency of agricultural production has been attested to by Chaovanapoonphol *et al.* (2005).

Farm households need credit to purchase external inputs, contract wage labour, acquire food and non-food items, invest in education, etc. (Ruben & Kolk, 2005). Access to credit also enables farmers to adopt more capital-intensive methods of production to improve their level of technical efficiency (Hazarika & AIwang, 2003). Alene & Hassan (2006) and Komicha & Öhlmer (2007) also indicate that the capacity of farmers to adopt improved production technologies can be constrained by resource limitations including credit constraints.

Capital market imperfections as a result of asymmetric information and problems of incentive compatibility have been identified as the cause of credit constraint encountered by borrowers (Stiglitz & Weiss, 1992; Blancard *et al.*, 2006). Alene & Hassan (2006) attest to credit market imperfections as common phenomena in developing countries due to poorly developed infrastructure, weak institutional environment and less competitive market situation.

Credit affects farm production both directly and indirectly. Directly, credit affords producers the purchasing power to acquire essential production inputs and carry out long-term investments. On the other hand, credit affects production indirectly through its effect on farmers' risk behaviour (Guirkinger & Boucher, 2005). For example, farmers who are credit constrained are more likely to invest in activities that are less risky and less productive. As indicated by Komicha & Öhlmer (2007), this risk behaviour can affect farmers' choice of technology and adoption decisions with implications for technical efficiency of the producers. Lack of credit can therefore serve as a binding constraint that limits investment in productivity-enhancing technologies and production inputs and limits the household's ability to reduce vulnerability (Owusu-Antwi, 2010).

It is evident from the foregoing that lack of credit can serve as a critical factor limiting productivity and efficiency of production of farm households. Recent studies on the effect of credit on efficiency, especially technical efficiency of production include Ayaz & Hussain (2011) who investigated the effect of institutional credit on the production efficiency of Pakistani farmers. The authors found credit to have a positive impact on technical efficiency. Pinheiro (1992) however found no effect of credit on technical, allocative and economic efficiency of farmers in Dominican Republic, while Chaovanapoonphol *et al.* (2005) found credit to reduce technical inefficiency of rice farmers in Thailand.

Studies on the efficiency of rice production in Ghana include Abdulai & Huffman (2000), Seidu *et al.* (2004), Al-Hassan (2008), and Martey *et al.* (2015). The results from these studies show high variability in the estimates of technical efficiency even for the same ecological zone. On the other hand, it is quite typical that average efficiencies may differ due to the method and sample used. The results from these studies however highlight considerable inefficiency of production which calls for measures that will improve the level of technical efficiency of Ghanaian farmers.

On the effect of credit on technical efficiency of Ghanaian farmers, we found very limited studies, which necessitated the current study. The few studies include Martey *et al.* (2015) who found a positive effect of credit on technical efficiency of maize producers in northern Ghana. Abdallah (2016) also investigated agricultural credit and technical efficiency of maize farmers in Ghana and found a positive effect of credit on efficiency.

To the best of our knowledge, there is no study that directly assesses the effect of credit on technical efficiency of rice production in Ghana. In most of the previous efficiency studies, a credit dummy has been included in the inefficiency effects model to explain the effect of credit on efficiency. The limitation of these approaches is that the selection bias arising from access to credit or credit participation is ignored which may lead to biased estimates of the impact of credit.

The credit impact assessment on technical efficiency requires that the researchers control for factors which influence participation in credit. One of the innovative approaches used by many researchers to account for selection bias, as in the case of credit-programme participation, is propensity score matching (PSM). Among the recent applications of PSM in agriculture are Mayen *et al.* (2010), Abdoulaye & Sanders (2013) and Abate *et al.* (2014). This sample selection method reduces the selection bias in programme participation, and therefore helps to obtain less unbiased estimates of the impact of an intervention or programme.

The current study therefore employs the propensity score matching technique to assess the effect of participation in microcredit on technical efficiency of smallholder farmers in northern Ghana. The participation in credit means that the household actually received credit from a particular source for the purpose of farming. By definition, microcredit refers to a limited amount of credit offered to poor people usually without collateral. The average loan received by the respondents in the current study suggests that the credit is micro in nature.

2 Materials and methods

2.1 *Theoretical background*

Economic theory stipulates that economic agents aim at output maximisation given the quantity of inputs and existing technology. This means that given fixed input levels, the producer must produce on or very close to the production frontier. Producers however differ in their ability to produce efficiently, that is, on the production frontier. Thus, with the same set of inputs, some producers will produce more output than others.

Different methods of estimating efficiency exist in the economic literature. The approaches can be categorised into parametric, semi-parametric and non-parametric ones (Chakraborty *et al.*, 1999). Unlike the parametric approach, the non-parametric method assumes no functional form. The parametric approach often employs stochastic frontier analysis (SFA) while the non-parametric approach typically employs data envelopment analysis (DEA). The stochastic frontier approach attributes deviations from the production frontier to inefficiency and random errors whereas the deterministic approach attributes all errors to inefficiency (Coelli *et al.*, 2005). The productive efficiency literature also distinguishes between technical, allocative, and economic efficiencies (see Khan & Saeed, 2011). We focus on technical efficiency in this study.

2.2 *The stochastic frontier model*

A firm is technically efficient in production if it is able to achieve maximum output, with given level of inputs and production technology. The stochastic frontier model assumes that maximum output may not be realised from a given set of inputs because of inefficiency. This model can be used to estimate efficiency and its determinants using either a two-step or a one-step procedure. The two-step procedure has been criticised for its theoretical inconsistency (see Kumbhakar *et al.*, 1991; Reifschneider & Stevenson, 1991), hence we apply the one-step procedure proposed by Battese & Coelli (1995) to estimate the parameters of the stochastic production frontier and inefficiency effects model using maximum likelihood estimation. The stochastic frontier production function is defined as follows:

$$Y_i = \exp(X_i\beta + V_i - U_i) \tag{1}$$

where Y_i is rice output, X_i is a vector of inputs, V_i is a symmetric error term indicating the effects of pure random factors on production, U_i is a one-sided error term indicating the effects of inefficiency and β is a vector of parameters to be estimated. Technical efficiency (TE) is computed as the ratio of the observed output Y_i to the frontier output Y_i^*.

$$TE_i = \frac{Y_i}{Y_i^*} = \frac{\exp(X_i\beta + V_i - U_i)}{\exp(X_i\beta + V_i)} = \exp(-U_i) \tag{2}$$

where $0 \leq TE \leq 1$. The technical inefficiency effects, U_i, are obtained by truncation (at zero) of the normal distribution with mean μ_i and variance σ_i^2 such that:

$$U_i = \delta_0 + \sum_{n=1}^{N} \delta_n Z_{ni} \tag{3}$$

where Z_i represents a vector of farm-specific independent variables and δ is a vector of unknown coefficients of the farm-specific inefficiency effects. We used the statistical software package Stata version 14 for the frontier analysis.

The study also conducted tests of the null hypotheses for the parameters in the production function and inefficiency effects model using the generalised likelihood-ratio test statistic defined as:

$$\lambda = -2\{\ln[LL_0/LL_1]\} \tag{4}$$

where LL_0 is the likelihood function under the null hypothesis and LL_1 is the likelihood function under the alternative hypothesis. For the test of functional form, the test statistic λ has approximately a Chi-squared or a mixed Chi-squared distribution. The difference between the number of parameters in the null and alternative hypothesis represents the degrees of freedom. For the inefficiency model, the critical values for λ are derived from Kodde & Palm (1986).

2.3 Propensity score matching and self-selection

Selection bias arises if the participation in credit by households is not random. Non-randomness in participation may arise if certain individuals are unable to participate or certain individuals decide not to participate. The failure to account for selection bias in credit participation is likely to lead to a biased estimate of the impact of credit.

The present study employs a matching approach (propensity score matching or PSM) to address the problem of self-selection. Matching models are a special case of selection models formulated on the assumption that conditioning on observable variables eliminates (or significantly reduces) sample selection bias (Heckman & Navarro-Lozano, 2004). Matching models create the condition of an experiment in which the treatment condition (i.e. participation in credit *versus* non-participation) is randomly assigned and provides a causal link between the treated group (e.g. credit participants) and the outcome of interest (i.e. technical efficiency).

The basic idea of the PSM method is to match observations of farmers with credit (the treated) and those without credit (the untreated) according to their predicted propensity of credit participation (Rosenbaum & Rubin, 1983; Heckman *et al.*, 1998). Rosenbaum & Rubin (1983) defined the propensity score as the conditional probability of receiving a treatment based on pre-treatment characteristics. It is expressed as

$$p(X) = \Pr\{L=1 \mid X\} = E\{L \mid X\} \tag{5}$$

where $L = \{0, 1\}$ represents the treatment indicator variable (e.g. participation in credit), E is the expectation sign (expected value) and X is a vector of pre-treatment characteristics such as farm and household characteristics.

We used the estimated propensity scores to obtain an estimate of the average treatment effect on the treated (ATT) which measures the effect of microcredit on participants. It is assumed that farmers have two potential technical efficiency outcomes, Y, given the participation status (L) such that $Y = Y_0$ if $L = 0$ and $Y = Y_1$ if $L = 1$. The average treatment effect (ATE) is represented by $ATE = E(Y_1 - Y_0)$. The average treatment effect on the treated (ATT), which is our variable of interest is given as $ATT = E\big((Y_1 - Y_0) \mid L=1\big)$. The ATT can further be expressed as $ATT = E(Y_1 \mid L=1) - E(Y_0 \mid L=1)$.

2.4 Empirical production frontier and probit models

The two most commonly used functional forms in efficiency analysis are the Cobb-Douglas and translog specifications. We conducted a formal test of the functional form and the Cobb-Douglas form was preferred above the translog specification. The current study therefore used the Cobb-Douglas production function in equation (6) to estimate efficiency of rice production in northern Ghana.

$$\ln Y_i = \beta_0 + \sum_{k=1}^{3} \beta_k D_{ki} + \sum_{j=1}^{6} \beta_j \ln X_{ji} + V_i - U_i \tag{6}$$

where Y_i represents rice output of the i^{th} farmer and j is the j^{th} input used in rice production. D_{ki} is the k^{th} intercept dummy variable where D_1 is an irrigation dummy, D_2 is a location dummy and D_3 is a cropping intensity dummy; ln = natural logarithm; X_1 = total land used for rice production; X_2 = total labour in man-days; X_3 = quantity of seed planted; X_4 = quantity of inorganic fertiliser applied; X_5 = other variable costs; X_6 = farm capital. V_i and U_i are as previously defined.

The technical inefficiency effect Ui is a linear function of socio-economic and management factors as defined in equation (7).

$$U_i = \delta_0 + \sum_{n=1}^{14} \delta_n Z_{ni} \tag{7}$$

where δ_n is the coefficient of the explanatory variables. Z_i represents farmer and household characteristics accounting for inefficiency in production. The Z_i variables included in the inefficiency model include the gender of the household head, age and its squared value, household size, contact with extension agents, educational status, association membership, participation in off-farm work, specialisation in rice production, distance to the nearest market, regional dummy, access to irrigation, participation in microcredit and herd ownership.

We specified the probit model for participation in credit as an index function, with an unobserved continuous variable (L_i^*) as follows:

$$L_i^* = \gamma Z_i + e_i \tag{8}$$

$$L_i = \begin{cases} 1 & \text{if } L_i^* > 0 \\ 0 & \text{if } L_i^* \leq 0 \end{cases}$$

where L_i = participation in credit (equals 1 for participants, 0 otherwise) and e_i is the random error term in the probit model. The explanatory variables included in the model are the gender, educational status, age, household size, total farm size, household income, access to irrigation (dummy), value of farm capital, adoption of improved variety (HYV dummy), association membership, distance to market, contact with extension (dummy), region (dummy), and awareness of lending/microfinance institutions (MFIs dummy). We used Stata version 14 to analyse credit participation and the propensity score.

2.5 Sampling and study area

The data used for the study came from a farm household survey conducted during the 2013/2014 farming season in northern Ghana. Northern Ghana is made up of three administrative Regions: Upper East, Upper West and Northern Region. Northern Ghana produces the bulk of the country's rice hence the choice of the location. The study involved 300 smallholder rice farmers distributed across northern Ghana.

We used a multi-stage stratified random sampling technique to select the respondents. First, we purposively selected two Regions, namely the Upper East and Northern Regions because of their contribution to domestic rice production and the presence of irrigation schemes for rice cultivation. After that, we selected three irrigation schemes based on size and geographical location. They included the Botanga Irrigation Scheme in the Northern Region and the Vea and Tono irrigation schemes in the Upper East Region. Next, we selected at random five communities within the catchment area of each irrigation scheme. Finally, we stratified the farmers into irrigators and non-irrigators, and selected equal number of respondents from each group. The study used a semi-structured questionnaire to solicit responses related to rice production, input and output quantities and prices, and whether the household participated in microcredit and the amounts borrowed.

3 Results

3.1 Characteristics of the respondents

Table 1 shows the descriptive statistics of the variables used in the study. About 40 percent of the sampled farmers participated in credit. As shown in the table, 104 credit users were matched to the non-credit users in the sample. In addition, credit users produced more rice and had higher household income than non-users. Credit participants also used more inputs in production with the exception of expenditure on other inputs.

Farmers in the Northern Region reported higher participation in credit while credit users had higher participation in farmer-based organisations. On the other hand, household size, educational status, age and herd size did not differ between credit participants and non-participants. Contrary to our *a priori* expectation, participants in credit devoted less land to rice cultivation while adoption of high-yielding varieties (HYV) was lower for credit users. Furthermore, one-third of credit users double-cropped their fields compared to one-quarter of non-users.

The amount of loan received by the respondents is shown in Table 2. Majority of the respondents took very small loans not exceeding GH₵200 with very few taking loans exceeding GH₵600. The average loan size was GH₵246.

The source of the credit included rural banks, government-subsidised credit targeted at poverty alleviation, non-governmental organisations working with farmers, farmers' cooperatives, relatives and moneylenders. Majority of the credit was collateral-free while subsidised credit from government sources, non-governmental organisations and farmers' cooperative had very low interest rates and limitations in terms of loan size. Very few farmers used credit from commercial sources. The loans were used primarily to finance land preparation and hiring in labour as well as the purchase of farm inputs notably fertilisers, chemical sprays and seeds. Majority of the farmers were credit-constrained as the loan amounts offered fell below the amount they actually requested. It was observed that farmers were reluctant to borrow from commercial sources which offer larger loan amounts. The lack of collateral and the high interest rates compared to the alternative credit sources, may account for this behaviour. Most of the non-commercial sources provided only limited amount of credit which may be due to the large number of applicants.

3.2 Propensity score matching analysis

We present the probit estimates of the credit propensity equation in Table 3. The model had a good fit as indicated by the pseudo-R^2, the percentage of correct predictions and the Chi-squared value.

Several variables included in the model had a significant effect on credit market participation. Female farmers and rain-fed producers were more likely to participate in credit, just as households with higher income and contact with extension agents. In addition, total household assets was positively related to credit participation while farmers who were aware of the presence of lending institutions in the area as well as farmers located in the Northern Region were more likely to participate in credit. However, contrary to our expectation we found participation in credit to increase with distance to the nearest market, while farmers who planted traditional varieties were also more likely to participate in credit.

Table 1: *Descriptive statistics of the variables used in the study*

Variable	*Credit-users* (N = 121)		*Non-credit users* (N = 179)		*Matched credit users* [a] (N = 104)		*t-test* [b]
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	
Output (kg)	1864	2285	1502	1962	1530	1661	1.466
Household income (Cedi) [c]	2796	2403	2073	1678	2467	2176	3.070***
Land area under rice (ha)	0.95	0.76	0.79	0.62	0.83	0.56	1.996**
Labour (man-days)	69.9	45.6	60.4	44.5	64.4	33.9	1.802*
Seed (kg)	186	179	139	134	172	164	2.617***
Inorganic fertiliser (kg)	317	370	275	321	292	360	1.047
Other costs (Cedi)	190	205	183	179	170	188	0.297
Farm capital (Cedi)	150	175	114	132	143	167	2.032**
Total household assets (Cedi)	728	1226	493.4	1001	636	1018	1.817*
Cropping intensity (1=double)	0.33	0.47	0.25	0.44	0.33	0.47	1.494
Sex (1=Male)	0.75	0.43	0.81	0.40	0.74	0.44	−1.079
Years of formal education	3.93	5.48	3.94	5.27	4.01	5.57	−0.021
Age (years)	41.9	12.0	40.7	12.5	41.4	12.4	0.841
Household size (number)	10.3	6.0	9.20	7.89	10.1	6.02	1.331
Total land area	7.05	5.94	4.79	4.09	5.98	3.86	3.895***
Access to irrigation (1=Yes)	0.50	0.50	0.50	0.50	0.49	0.50	0.117
Adopt improved variety (1/0)	0.59	0.49	0.72	0.45	0.60	0.49	−2.429**
Group membership (1=Yes)	0.75	0.43	0.60	0.49	0.73	0.45	2.794***
Share of land under rice (%)	38.9	20.7	49.7	26.9	39.2	20.6	−43.735***
Herd ownership (1=Yes)	0.37	0.49	0.31	0.46	0.37	0.48	1.060
Distance to market (km)	7.49	4.42	8.21	4.21	7.91	4.58	−1.414
Extension contact (1=Yes)	0.72	0.45	0.58	0.50	0.69	0.46	2.551**
Regional dummy (1=Northern)	0.45	0.50	0.25	0.44	0.40	0.49	3.734***
Awareness of MFIs [d] (1=Yes)	0.92	0.28	0.74	0.44	0.90	0.30	3.884***

***, ** and * stand for statistical significance at the 1, 5 and 10 percent level, respectively. [a] The subsample of credit participating farms matched to non-participating farms on the basis of the estimated likelihood or propensity of participating in credit. [b] The test of mean difference between the unmatched groups. [c] GH₵1 = US$0.26. [d] MFI means microfinance institution.

Table 2: *Amount of loan received by respondents*

Loan size (GH₵)*	*Frequency*	*Percentage*	*Cumulative* (%)
1–200	69	57.0	52.0
201–400	30	24.8	81.8
401–600	15	12.4	94.2
601–800	5	4.1	98.4
801–1000	2	1.7	100.0
Total	121	100.0	100.0

*1GH₵ is equivalent to US$0.26.

Table 3: *Probit results of the determinants of access to agricultural microcredit*

Variable	*Coefficient*	*Std. Error*	$P>\|z\|$
Sex	−0.666***	0.225	0.003
Education	0.017	0.016	0.298
Age	0.008	0.007	0.281
Household size	−0.023	0.014	0.103
Land	0.022	0.022	0.320
Household income	0.189*	0.112	0.092
Access to irrigation	−0.344*	0.188	0.068
Total household assets	0.115**	0.048	0.016
Improved variety adoption	−0.455**	0.183	0.013
Group membership	0.128	0.193	0.507
Distance to market	−0.038*	0.021	0.071
Extension contact	0.710***	0.210	0.001
Regional dummy	1.337***	0.243	0.000
Awareness of MFIs	1.094***	0.258	0.000
Constant	−1.490***	0.518	0.004

***, ** and * stand for statistical significance at the 1, 5 and 10 percent level, respectively. Number of observations = 300, Log-likelihood = −158.7, Wald Chi^2 (14) = 87.22, Prob > Chi (2) = 0.000, Pseudo R^2 = 0.216, Percentage correctly predicted = 71.3.

We used the estimates of the probit model to obtain a propensity score (the predicted probability of participation in credit) for each farm after which each credit-participant was matched to a non-participant with similar propensity score. The propensity score matching technique produced a subsample of 283 matched farms comprising 104 credit participants and 179 non-participants. We used this new sub-sample to estimate the production frontier. We ensured that the matched samples were within the common support region to ensure the robustness of the matching. As indicated earlier, the common support region indicates values of the propensity scores where the treated (credit users) and untreated units (non-credit users) can be found. Without a common support, suitable matches are unlikely to be obtained. We present a plot of the treated and untreated units after the matching in Figure 1. The plot shows the propensity scores on the x- axis with the matched treated units above the horizontal line and untreated units below the horizontal line.

To check the robustness of the propensity score matching, a balancing test of the matched sample was performed and the results are reported in Table 4. The balancing test is a test of the mean equality of the covariates for credit users and non-users before and after the matching. The results indicate that the unmatched sample does not to satisfy the balancing property as the

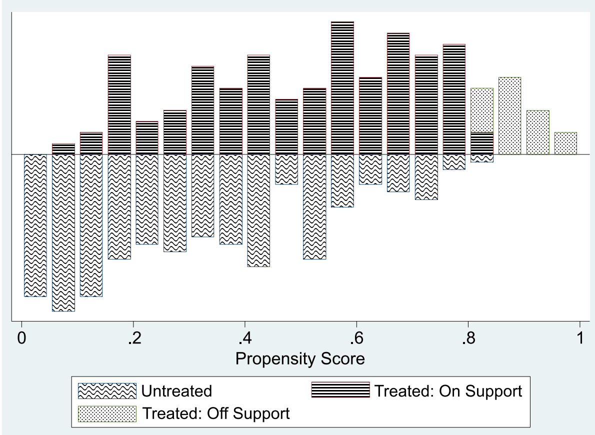

Fig. 1: *Distribution of common support region by treatment status (Note: The treated are the credit users)*

two groups are comparable in only 6 out of the 14 covariates. The matched sample however showed no systematic differences in the observed covariates between credit users and non-users thus justifying the validity and robustness of the matching.

3.3 Tests of hypotheses

We present the results of the tests of hypotheses regarding the functional form and inefficiency effects model in Table 5. From the results, we adopt the Cobb-Douglas functional form and reject the null hypothesis of no inefficiency effects in the specified model implying that the traditional average response model is not an appropriate representation of the data. The result of the second assumption indicates that the variables included in the inefficiency effects model jointly measure production inefficiency of the respondents.

3.4 Estimation of technical efficiency and its determinants

We present in Table 6 the maximum-likelihood estimates of the parameters of the Cobb-Douglas stochastic frontier and inefficiency models based on the PSM subsample. All the conventional inputs maintained a positive sign in line with our *a priori* expectation. Furthermore, all the conventional inputs apart from capital and labour had a significant effect on rice production. This shows that the size of farm, seed, fertiliser and other costs positively influence the output of smallholder rice producers in northern Ghana. The intercept dummies included in the model to account for shifts in the production function were statistically significant. Irrigators as well as producers in the Northern Region and households who double-cropped their land had a higher production frontier.

Table 4: *Balancing test of matched sample*

Variable	*Unmatched Sample*			*Matched Sample*		
	Mean		*Diff: $P>\|t\|$*	*Mean*		*Diff: $P>\|t\|$*
	Treated	*Control*		*Treated*	*Control*	
Sex	0.752	0.804	0.281	0.740	0.762	0.718
Education	3.926	3.939	0.984	4.010	3.975	0.963
Age	41.93	40.72	0.401	41.41	40.57	0.619
Household size	10.32	9.196	0.184	10.06	9.508	0.578
Land	7.047	4.790	0.000	5.976	6.296	0.628
Household income	2796	2073	0.002	2467	2491	0.934
Access to irrigation	0.504	0.497	0.907	0.490	0.466	0.723
Total household assets	728.0	493.4	0.070	636.2	653.8	0.910
Improved variety adoption	0.587	0.721	0.016	0.596	0.604	0.907
Group membership	0.752	0.598	0.006	0.731	0.647	0.193
Distance to market	7.492	8.207	0.158	7.909	7.915	0.992
Extension contact	0.719	0.575	0.011	0.692	0.652	0.534
Regional dummy	0.455	0.251	0.000	0.404	0.412	0.903
Awareness of MFIs	0.917	0.743	0.000	0.904	0.919	0.698

Note: The treated are the credit users.

Table 5: *Generalised likelihood-ratio tests of hypotheses*

Null hypothesis	*LR statistic (λ)*	*Critical value* *	*Decision*
Production function is Cobb-Douglas	30.6	32.7	Accept H_0
No inefficiency effects: $H_0 : \delta_0 = \delta_1 = \ldots = \delta_{12} = \gamma = 0$	59.9	25.7	Reject H_0
Inefficiency model does not explain inefficiency: $H_0 : \delta_0 = \delta_1 = \ldots = \delta_{12} = \gamma = 0$	55.0	24.4	Reject H_0

* We obtained critical values for the inefficiency model from Kodde & Palm (1986)

A 1 % increase in land area increased output by 0.31 % while a 1 % increase in labour and seed increased output by 0.15 % and 0.16 % respectively. In addition, a 1 % increase in fertiliser, other costs and capital increased output by 0.07 %, 0.09 % and 0.01 % respectively. Land had the highest effect on output followed by seed and labour. Capital had the least effect on output while the sum of the coefficients of the input variables, which is a measure of economies of scale, was 0.79. The result implied diminishing returns to scale in rice production.

The inefficiency effects model in Table 6 shows that male farmers recorded higher efficiency than female farmers. Efficiency increased with age but later decreased with the progression in age. Thus, there is an increase in efficiency with age but at a decreasing rate. Farmers who allocated a greater portion of their land to rice cultivation as well as herd owners were also more efficient in production. In addition, efficiency was higher for farmers in the Northern Region and for users of irrigation. Finally, efficiency decreased with the educational level of the household head but increased with the distance to the nearest market.

Table 6: *Maximum likelihood estimation results of the stochastic frontier production function and inefficiency effects model*

Variable	*Parameter*	*Coefficient*	*Standard Error*	*p–value*
Constant	β_0	−0.170	0.118	0.149
Cropping intensity dummy	β_{01}	0.259 **	0.102	0.011
Irrigation dummy	β_{02}	0.257 **	0.103	0.012
Regional dummy	β_{03}	0.581 ***	0.107	0.000
Land	β_1	0.313 ***	0.104	0.003
Labour	β_2	0.146	0.097	0.135
Seed	β_3	0.160 **	0.068	0.019
Fertiliser	β_4	0.067 **	0.026	0.010
Other costs	β_5	0.089 ***	0.030	0.003
Capital	β_6	0.010	0.031	0.747
Inefficiency model				
Constant	δ_0	4.710 ***	1.540	0.002
Participation in credit	δ_1	−0.039	0.265	0.882
Sex of household head	δ_2	−1.138 ***	0.340	0.001
Age of household head	δ_3	−0.113 *	0.067	0.090
Age squared	δ_4	0.001 *	0.001	0.077
Household size	δ_5	−0.019	0.023	0.391
Extension contact	δ_5	−0.119	0.296	0.688
Years of formal education	δ_7	0.049 **	0.025	0.049
Association membership	δ_8	−0.383	0.264	0.146
Share of land under rice	δ_9	−0.013 **	0.007	0.041
Distance to nearest market	δ_{10}	−0.064 **	0.032	0.044
Herd ownership	δ_{11}	−0.818 **	0.367	0.026
Regional dummy	δ_{12}	−0.799	0.580	0.168
Irrigation dummy	δ_{13}	−0.849 **	0.382	0.026
Off-farm work	δ_{14}	0.062	0.248	0.802
Variance parameters				
Sigma-squared	σ^2	0.893 ***	0.057	0.000
Gamma	γ	0.719 ***	0.012	0.000
Log likelihood function	λ	−239.6		
Returns to scale		0.785		

***, ** and * stand for statistical significance at the 1, 5 and 10 percent level, respectively.

3.5 *Difference in technical efficiency between credit participants and non-participants*

The estimated mean technical efficiency for the PSM subsample was 63.0 % (SE 0.019) for credit users and 61.7 % (SE 0.016) for non-users. The means were not statistically different. We used nearest-neighbour matching to estimate the propensity score and the average treatment effect on the treated (ATT). The result indicates a non-significant effect of microcredit on smallholders' technical efficiency (ATT of 0.013, SE 0.031) which is consistent with the results obtained using the PSM subsample.

4 Discussion

4.1 Propensity score analysis

The study indicates that women farmers are more likely to take part in microcredit. This result is supported by Jazairy *et al.* (1992) who found female borrowers to be more creditworthy. Akudugu (2012) also found that women were more likely to demand credit than men in the Upper East Region of Ghana. Furthermore, increasing farmers' awareness of the presence of lending institutions promotes their participation in credit programmes. The result agrees with Gaih & Thapa (2006) who reported that lack of awareness is a factor excluding some groups from microfinance. The results of the study also highlight the positive effect of extension contact on smallholders' participation in credit. Contact with extension agents enhances farmers' knowledge about the presence of lending institutions and the sources of credit thereby facilitating their participation in microcredit programmes. The result is consistent with Muhongayire *et al.* (2013) who found extension contact to enhance farmers' participation in formal credit in rural Rwanda.

The greater participation of households with higher income (and larger total household assets) in microcredit suggests that wealth status could affect smallholders' participation in rural credit programmes. As indicated by Anang *et al.* (2015), some lenders may consider poor households as risky borrowers thus constraining their participation in microcredit. The reasons behind the effects of market distance, geographical location and choice of rice variety on credit participation were not obvious. Finally, the lower participation rate of irrigators in credit indicates that agricultural microcredit may be seasonal and less available during the dry (off) season when irrigation farming is mostly practiced. The reason may also be that irrigators get more frequent returns from farming and therefore face less liquidity constraints.

4.2 Technical efficiency and its determinants

The intercept dummy variables included in the production function suggest that participation in irrigation, cropping intensity and location of the farm (Northern Region = 1) shifted the production frontier upwards. In other words, irrigators, farmers who double-cropped their farms and farmers in the Northern Region operate on a higher production frontier which implies higher productivity.

All the conventional inputs had a positive effect on rice output in line with the monotonicity assumption of production functions. The area of land under rice production had the highest impact on rice output compared to the other variable inputs as shown by the estimated output elasticity with respect to land. Capital had the least effect on output and this may be due to the low use of capital inputs by the farmers. The study also revealed diminishing returns to scale in rice production. Thus increasing all inputs by 1 % will increase rice output by 0.79 %.

The result of the study also indicates women's lower efficiency of production relative to men, which is consistent with Abdulai *et al.* (2013) and Donkoh *et al.* (2013). Many researchers have recognised the important role of women as agricultural producers. However, gender inequality in access to production technology in many developing countries means that women farmers are often disadvantaged which can adversely affect their level of efficiency. Women also face other challenges that have negative impact on their technical efficiency. As shown by Abdulai *et al.* (2013), women's domestic and economic roles tend to affect their technical efficiency in farming.

Technical efficiency of production also tends to increase with the age of the household head. The result suggests that older farmers who are likely to be more experienced in farming utilise resources more efficiently in production. However, with progression in age, productivity begins to decrease as farmers become less energetic. The result agrees with Taiwo *et al.* (2014) who found that efficiency in cassava production in Nigeria increased with age but declined as farmers became very old. If the household head is older, there is the likelihood that the family labour may increase as the children become older. However, this may not be the case in the situation where the older children out-migrate. Participation in off-farm work may also decrease family labour for farming activities. Hence, there is the likelihood that family labour is getting less in the current study area and thus having adverse effect on efficiency as the household heads grow older.

Farmers' technical efficiency also increased with participation in farmers' organisations which is consistent with our *a priori* expectation. Farmers belonging to a farmers' group benefit from economies of scale, the sharing of production information, and access to production inputs and agricultural extension service, thus enhancing their efficiency in production. The result is consistent with Shehu *et al.* (2010) who reported that association membership enables yam farmers in Nigeria to access loans and productive inputs, which are easier to obtain collectively than individually. Idiong (2007) also found membership of farmers' association to increase the technical efficiency of Nigerian cocoyam farmers due to information sharing among members.

Farmers who allocated a greater proportion of their land to rice cultivation were more efficient in production because of specialisation. The result is in line with classical economic theory which views specialisation as an important determinant of efficiency. The study also highlighted the importance of draught animals (animal traction) in smallholder production and efficiency. Households having cattle were more efficient in production because the use of draught animals (cattle) enabled timely and more efficient farm operations.

Education, which is an important part of human capital, improves the quality of labour (Hyuha *et al.*, 2007). Education is therefore expected to improve the technical efficiency of farmers. The lower efficiency level of educated farmers in the current study may be due to the fact that educated farmers are more likely to find jobs outside the farm sector, which may interfere with the time they allocate to farming activities. Donkoh *et al.* (2013) and Asante *et al.* (2014) found similar effect of education on the efficiency of smallholder rice production in Ghana.

The distance to the nearest local market exerted a positive influence on technical inefficiency contrary to our *a priori* expectation. This shows that farmers living further away from the local market are more efficient in production. The longer distance to markets is likely to affect the timely acquisition of farm inputs to carry out farm operations which can affect technical efficiency. The result of our study agrees with Martey *et al.* (2015) who found that the technical efficiency of Ghanaian maize farmers increased with an increase in the distance to the local market.

Irrigation users also had higher efficiency of production than non-irrigators. Access to irrigation enables farmers to maximise the use of other inputs such as fertiliser due to the availability of water throughout the farming season. The result is consistent with other research findings (Makombe *et al.*, 2007; Mariano *et al.*, 2011).

4.3 Effect of credit on technical efficiency

The main objective of the study was to compare the mean efficiency of credit users and non-users. We found the mean efficiency for credit users to be statistically not different from non-users. Furthermore, the result of the average treatment effect on the treated which measured the impact of credit on participants in microcredit programme showed no significant impact of credit on technical efficiency. A possible reason for the insignificant effect of microcredit on technical efficiency may be the small size of credit as shown in Table 2. By relaxing the liquidity constraints of farmers, credit helps producers to hire in labour and buy other production inputs that may enhance their technical efficiency. The small amount of credit to the respondents in the current study may therefore be insufficient in augmenting their technical efficiency. Hence increasing the loan size given to farmers could improve technical efficiency of rice production in northern Ghana.

5 Conclusion

The study investigated the effect of microcredit on technical efficiency of smallholder rice production in northern Ghana using cross-sectional data from 300 farm households. The study involved the estimation of a credit participation model and a Cobb-Douglas production function. We controlled for self-selection using propensity score matching and found that efficiency did not differ between credit-participating and non-participating farms although it was slightly higher in the credit-participating group. Controlling for self-selection using the PSM approach to match farmers based on their observed characteristics ensured that we obtained a more reliable comparison of technical efficiency for both participants and non-participants. The insignificant effect of credit on technical efficiency may be due to the small size of loans. From the results of the study, we conclude that credit should be channelled to farmers who demonstrate the need for it and show the commitment to improve their production through external financing. Such a screening mechanism will ensure that credit goes to the right farmers who have need for it to improve their technical efficiency. Credit institutions may also consider providing credit in kind rather than in cash to make inputs readily available to farmers as well as minimise the possibility of channelling the credit into other uses. Finally, improving access to irrigation and enabling intensification of production are possible options to improve productivity of rice farmers in the study area.

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