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SCIENTIFIC PAPER

OFF-FARM PARTICIPATION AND TECHNICAL EFFICIENCY AMONG SMALLHOLDER FARMERS IN THE NORTHERN REGION, GHANA

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Abstract: *The study aimed at investigating the effects of off-farm participation on technical efficiency of maize production in the Tolon district of the Northern Region, Ghana. The Logit regression model was used to analyze the determinants of off-farm participation while the stochastic frontier production function was used to model the determinants of maize output and technical efficiency. The empirical results from the logistic regression model indicate that age of farmer, educational attainment, farming experience, farm size, and previous farm income are significant drivers of farmers' participation in off-farm activities. Farmers' average technical efficiency level was 90.7% suggesting a 9.3% potential loss to inefficiency. Moreover, participation in off-farm activities had a negative influence on farmers' technical efficiency level. The study, therefore, recommends that farm-level policy should be directed towards making the agricultural sector attractive by promoting investment and agricultural employment opportunities in the rural areas so as to ensure full commitment to farming activities.*

Keywords: *Logit model; Northern Ghana; Off-farm participation; stochastic frontier model; Technical efficiency;*
(JEL code: *Q22*)

INTRODUCTION

Maize production in Ghana has seen significant improvements with an average production of 1.4 million metric tonnes over the period 2005 – 2010 (Ministry of Food and Agriculture, Ghana [MOFA], 2011). Such an impressive performance could partially be attributed to factors such as favourable rainfall pattern, the introduction of subsidy, high food prices which could have stimulated domestic prices over the period 2008 – 2010. Nevertheless, the actual yields observed fall short of the potential yield in the maize industry. The observed yield of about 1.9mt/ha is about 70% less than its potential yield of about 6mt/ha (MOFA, 2013). Thus, the impressive performance of the maize sub-sector was driven by land expansion rather than increase in yield. The lower yields have been partially attributed to poor soil fertility, erratic rainfall pattern, the use of traditional farming practices, low-yielding varieties and inappropriate control of weeds as well as inadequate capital to purchase inputs. However, a major hindrance to the adoption of most of these productivity-enhancing inputs has been the lack of liquid capital to finance the acquisitions of the inputs (Byerlee et al. 2005).

One of the most significant challenges facing agricultural production in developing countries like Ghana has been the need to raise farm incomes through increased agricultural productivity. Many farm households often resort to alternative means like off-farm activities to deal with the challenges of income variability. Off-farm activities have therefore become an essential component of livelihood strategies of many rural households in Ghana. One of the reasons for farmers' engagement in this income diversification is to guide against agricultural production and market risks (Ellis et al. 2004). Thus, when farm business becomes less profitable, farm households are likely to be pushed into off-farm business leading to *"distress push"* income diversification. On the other hand, households get into off-farm activities when return to off-farm employment is greater and less risky than agricultural employment, leading to *"demand pull"* diversification.

Moreover, off-income opportunities have been identified as an important strategy for overcoming credit constraints faced by farmers in most rural areas of many developing countries (Readon et al. 2007). However, many pieces of literature on the linkage between off-farm income and agricultural production have presented mix conclusions. One strand of literature (Babatunde and Qaim 2010) argues that off-farm income may help to increase agricultural production, serve as collateral to credit accessibility and could even be used as a substitute for borrowed capital in rural economies with imperfect credit markets. However, another school of thought argues that off-farm income may undermine farmers' adoption of modern technologies (especially labour-intensive technologies) by reducing the amount of household labour allocated to farming activities (Godwin and Mishra 2004; Mcnally, 2002). The study, therefore, seeks to investigate the effects of off-farm participation on crop productivity and technical efficiency using maize farmers in the Tolon District of the Northern Region of Ghana as a case study.

There is a paucity of knowledge in African agricultural economics literature on off-farm income and its effect on productivity and technical efficiency. In-depth knowledge in this regard could help policy planners develop better strategies relative to farm development programmes. In the Northern Region of Ghana, production, and marketing of crop serves as a source of livelihood for many people. Therefore, any study that aims to inform policy planners on ways to increase maize yield will go a long way to better the lives of the rural farm households. The remainder of this paper has been organized into four sections. Section one provides both theoretical and empirical literature review. The methodology is presented in the next section. In section three, we discuss the empirical results from the study. The final part of the paper ends with conclusions and recommendations for policy and future studies.

METHODOLOGY

The study area, sampling technique and data type

The study was carried out in the Tolon district in the Northern region of Ghana. The district lies between latitude 90-201 degrees North and longitude 10-50 degrees west. The district is in the guinea savannah zone with a single rainfall season. Annual rainfall is about 100 mm with temperature ranging from 17- 40 degrees in a year (Tolon District Agriculture Profile, 2013). The district has a total population of 22,990 with farming as their primary occupation. A multi-stage sampling technique was employed in the study. At the first stage, random sampling was used to select eight communities from the district. Secondly, fifteen respondents stratified into off-farm income earners and non-off-farm income earners were selected from each community giving a total sample size of one-hundred and twenty (120). Semi-structured questionnaires were used to collect primary data from the respondents serving as the unit of analysis.

Conceptual framework and estimation technique

In this study, we employed the framework of individual time allocation proposed by Huffman (1991), where farm households allocate their time to various activities including off-farm businesses. According to this model, a person is assumed to maximize his/her utility (U) given the consumption of goods (Y) and leisure (L) such that, $U_i = U(Y, L)$ and this utility is maximized subject to time, budget, production, and non-negativity constraints. The time constraint is given as, $T = l_f + l_{of} + L$, where l_f, l_{of} and L represent time allocated to farm work, off-farm work, and leisure, respectively. Further, the budget constraint on household cash income is expressed as,

$$PY = p_1 q_1 + w_1 l_f + w_2 l_{of} + I \qquad (1)$$

where P denotes the price of consumption of goods purchased at the market, p_1 and q_1 are respectively the price and quantity of output produced annually, w_1 and w_1 are labour wages attributed to farm and off-farm work and I represent non-labour income. The return to labour from the first order condition can be obtained as, $(\partial U/\partial l)/(\partial U/(\partial Y)$.

The labour supply function with respect to time allocation to farm work and off-farm work can be expressed as;

$$l_f = l_f(w_1, w_2, p_1, p_2, X) \qquad (2)$$

$$l_{of} = l_{of}(w_1, w_2, p_1, p_2, I, X) \qquad (3)$$

omic and other non-socioeconomic characteristics influencing their reservation and off-farm wages. Huffman (1991) observed that an individual farmer will engage in off-farm activity if the potential market wage (w_i^m) is greater than the reservation wage (w_i^r).

Thus, $l_i = 1,\ if\ w_i^m > w_i^r$ and $l_i = 0\ if\ w_i^m \leq w_i^r$.

Nevertheless, this differential wage rate cannot be observed by the researcher. What can be observed is the farmer's decision to participate in an off-farm business which can be expressed as an index function with unobserved variables shown in equation (4).

$$l_i^* = \beta X^{/} + \varepsilon_i$$

$$l_i = 1 if\ l_i^* > 0 \qquad (4)$$

$$l_i = 0 if\ l_i^* \leq 0$$

where ε represents the disturbance term.

The study employed three approaches to estimate the effect of off-farm income participation on technical efficiency. First, farmers' engagement in off-farm businesses as a choice variable was modelled. Secondly, we corrected for the endogeneity of off-farm participation by predicting its probabilities. In step three, we used the predicted probabilities as a regressor in the technical inefficiency model; after which a single stochastic frontier was estimated. The coefficient of the off-farm participation variable was used to assess the effect of farmers' engagement in off-farm activities on technical efficiency. Asante et al. (2014) applied the same technique to estimate the effect of yam minisett technology on technical efficiency of yam farmers in the forest-savannah transition zone of Ghana. The mean difference in technical efficiency between participants and non-participants of off-farm economic activities as well as a likelihood ratio test were used to assess the technical efficiency effects of off-farm participation further.

Estimating off-farm work participation

In this study, a farmer is said to have engaged in off-farm work if, in addition to crop farming, he/she engages in any non-agricultural activity such as trading or salary work. This study adopted the logistic regression to model the determinants of off-farm business participation in the study area. The response variable (dependent) was binary; taking values of one (1) if a farmer was into an off-farm business and zero (0) otherwise. However, the independent variables were both discrete and continuous. According to Gujarati (2005), logistic regression is simple in terms of its calculation, and its probability lies between 0 and 1. Another advantage of using logit model is that its estimates are consistent, efficient, do not require normally distributed variables, and above all, they are flexible to compute and interpret. The probability that a farmer will engage in at least one off-farm business was postulated to be a function of some socio-economic, farm-specific and institutional factors. Hence, the cumulative logistic probability model can be econometrically specified as;

$$\begin{aligned} P_i(y_i = 1/x_i\beta_i) &= 1 - e^{-x^1\beta} /(1 - e^{x^1\beta}) \\ &= e^{x^1\beta} /(1 + e^{x^1\beta}) \end{aligned} \quad (5)$$

The binary model as a regression model is written as:

$$y_i = 1 - f(x_i\beta) + \varepsilon_i \quad (6)$$

where y_i is the dependent variable denoting farmers' participation in off-farm business and X_i is a vector of factors influencing such participation. ε_i is a residual representing the deviation of the binary from its conditional mean. The empirical logit model specified to analyse the determinants of off-farm participation of farmers in the study area can be expressed as;

$$\begin{aligned} A_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \\ \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \varepsilon_i \end{aligned} \quad (7)$$

where A_i is the probability of off-farm participation, X_1 denotes gender of the farmer, X_2 age of the farmer, X_3 the square of the age of the farmer, X_4 household size, X_5 educational level of the farmer, measured in years, X_6 cocoa farming experience, X_7 farm size, and X_8 value of farm output (farm income).

Estimating technical efficiency of maize farm households

Farm technical efficiency is the ability of a farmer to maximize output with a given quantity of inputs and a certain technology (output-oriented) or the ability to minimize input use with a given objective of output (input-oriented). However, the output-oriented technical efficiency is commonly used. Following the work of Aigner et al. (1977) and Meeusen and Van den Broeck (1977), the stochastic production function for a given farm can be specified as;

$$Q = f(X;\beta) + V_i - U_i \quad (8)$$

where Q, X, β are maize output in kilograms, vector of inputs and the estimated parameters, respectively.

V_i captures the stochastic effects outside the farmers' control, measurement errors and some statistical noise and U_i captures farmers' inefficiency effects. The possible production Q is bounded by the stochastic quantity, hence the name stochastic frontier. V_i is a random error, assumed to be independent and identically distributed as $N(\mu,\sigma^2)$,. U_i is non-negative technical inefficiency effect assumed to be independent among them and between the $V_i s$. U_i is defined by the truncation of the $N(\mu,\sigma^2)$ distribution where it is defined by socio-economic and farm-specific variables postulate to explain the variations in technical efficiencies. Technical efficiency of the i^{th} farm is the observed output Q^* to that of the corresponding frontier output Q. Thus;

$$TE = \frac{Q_i}{Q_i^*}, Q_i = f(X_i;\beta)\ ,\ TE = \exp(-U) \quad (9)$$

$$\text{Technical inefficiency} = 1\text{-}TE \quad (10)$$

Q_1 is the observed output and Q_1^* is the unobserved frontier production level. This is such that $0 < TE < 1$. The parameters of the stochastic production function frontier were estimated by the maximum likelihood function using STATA 13. The maximum likelihood estimates of the stochastic frontier model provide the estimates of β and the gamma, where (γ) the gamma explains the variation of the total output from the frontier output.

The gamma estimate is specified as, $\gamma = \frac{\sigma_u^2}{\sigma^2}$.

Where γ lies between zero and one $(0 \le \gamma \le 1)$, σ_u^2 is the variance of the error term associated with the inefficiency effect and σ^2 is the overall variation in the model specified as the sum of the variance associated with the inefficiency effect (σ_u^2) and that associated with random noise factors (σ_v^2). Thus, $\sigma^2 = \sigma_u^2 + \sigma_v^2$. The closer the value of the gamma is (γ) to one (1), the greater the deviation of the observed output from the deterministic output which is because of inefficiency factors. However, if the value is close to zero, then the deviations result from random factors and if the value lies between one (1) and zero (0), then the deviations are as a result of both inefficiency and random factors.

Empirical model

The empirical model for the stochastic transcendental production function can be specified as;

$$\ln Q_i = \beta_0 + \sum_{j=1}^{5} \beta_j \ln X_{ji} + \frac{1}{2}\sum_{j\geq}^{5}\sum_{k=1}^{5} \beta_{jk} \ln X_{ji} \ln X_{ki} + V_i - U_i \quad (11)$$

where Q denotes the output of maize, X_i is a vector of inputs used in maize production which include family labour, hired labour, the quantity of fertilizer, herbicides, and farm size. β_j is the parameter to be estimated and ε_j is the error component. The translog functional form was selected for this study after a preliminary test that suggests it is more appropriate than the Cobb-Douglas functional form. The translog has an advantage over the Cobb-Douglas in that it does not place any restriction on the elasticity of production, hence its flexibility. Studies such as Adzawla et al. (2015); Mekonnena et al. (2015); Asante et al. (2014); among others have used the translog production function to estimate technical efficiencies in the Ghanaian agricultural crop sector.

Input elasticities and returns-to-scale

In estimating the elasticity of output with respect to inputs, the variables included in the translog stochastic frontier were mean-corrected by subtracting the mean of the variable from their individual values. The elasticities of mean maize output in the translog production frontier for different inputs are a function of some parameters and values of the inputs. According to Battese and Broca (1997), the elasticity of mean maize output with respect to some *jth* input can be expressed as follows;

$$\frac{\partial \ln E(Y_i)}{\partial \ln X_{ji}} = \left\{\beta_j + \sum_{k=1}^{5} \beta_{jk} \,\mathrm{h}\; X_{ki}\right\} - C_i\left(\frac{\partial U_i}{\partial \mathrm{h}\; X_{ji}}\right) \quad (12)$$

The first component of the right-hand side of the equation above is called the *elasticity of frontier output* with respect to the *jth* inputs in the model. The second component is referred to as *the elasticity of technical efficiency* with respect to input included in the model.

U_i is the inefficiency model;

$$C_i = 1 - \frac{1}{\sigma}\left\{\frac{\phi\left(\frac{U_i}{\sigma} - \sigma\right)}{\varphi\left(\frac{U_i}{\sigma} - \sigma\right)} - \frac{\phi\left(\frac{U_i}{\sigma}\right)}{\varphi\left(\frac{U_i}{\sigma}\right)}\right\}; \quad (13)$$

where ϕ and φ represent density and distribution functions of the standard normal random variable, respectively. However, since none of the conventional inputs in the production function is also involved in the technical inefficiency model, elasticity of technical efficiency is expected to be zero. Return-to-scale (RTS) is expressed as the summation of the elasticities, thus;

$$RTS = \sum_{j=1}^{5} X_j \quad (14)$$

If *RTS* is greater than one (*RTS > 1*) it means there are increasing returns-to-scale, if it is equal to unity (*RTS = 1*) also implies constant returns-to-scale and if *RTS* is less than one (*RTS < 1*), there are decreasing returns- to-scale.

Specification of hypotheses

In estimating the stochastic maize production function, we performed three main null hypotheses to examine the appropriateness of the specified model used, the significance of exogenous variables in explaining inefficiency and the significant effects of off-farm activities on technical efficiency. The three null hypotheses are presented as follows;

$$H_0 : \beta_{jj} = \beta_{ji} = 0$$

The coefficients of the squared values and the interaction terms in the translog model sum up to zero

$$H_0 : \delta_0 = \delta_1 = ...\delta_{10} = 0$$

Exogenous factors are not responsible for the inefficiency term μ_i

$$H_0 : \beta_1 = 0$$

The probability of maize farmers' participation in off-farm activities has no significant effect on technical efficiency.

These hypotheses were tested by using the generalized likelihood-ratio test statistic specified as;

$$LR(\lambda) = -2[\{\ln L(H_0)\} - \{\ln L(H_1)\}] \quad (15)$$

where $L(H_0)$ and $L(H_1)$ are the likelihood functions under the null and the alternate hypotheses, respectively. If the given null hypothesis is true, then the test statistic (γ) has a chi-square distribution with a degree of freedom which is equal to the difference between the estimated parameters under (H_1) and (H_0).

However, if the null hypothesis involves $\gamma^1=0$, then the asymptotic distribution involves a mixed chi-square distribution (Coeli, 1995).

Estimating the effects of off-farm business on technical efficiency

To measure the effects of off-farm income on TE, we follow Asante et al. (2014) by predicting the probability of off-farm income after modelling off-farm participation as choice variable and estimated its determinants. The predicted probabilities of off-farm participation were then regressed together with other socioeconomics, farm-level and other institutional variables in the maize stochastic frontier inefficiency model. This approach was employed to correct for endogeneity in off-farm participation before inserting into the technical efficiency estimation. The technical inefficiency model can be express as;

$$U = \beta_0 + \beta_j \sum_{j=1}^{4} X_j + \alpha_i OFI_j + \varepsilon_j \quad (14)$$

where; X_1, X_2, X_3, and X_4 represent farmers' age, distance to farm, educational level, and farmers' experience, respectively. OFI_i denotes predicted off-farm income probabilities and ε represents the error term. We then estimate a single stochastic frontier for off-farm beneficiaries and non-beneficiaries and the mean technical efficiency scores were used as a robustness check of the effects of off-farm income on technical efficiency.

RESULTS AND DISCUSSIONS

Determinants of off-farm activity participation

As indicated earlier, the logistic regression model was used to determine the factors influencing off-farm participation in the study area. From Table 1, the Pseudo R^2 value of 0.7369 implies that 73.69% of the variation in the probability of engaging in off-farm activities was explained by the factors included in the model. The results of the logistic regression analysis shown in the Table demonstrate that age, age squared, the number of years in formal education, the number of years in maize farming, land size allocated to maize production, and the previous output of maize exert significant effects on off-farm participation. The coefficient of age and the age squared of the household head exert significant positive effects at 5% significant level on off-farm employment. This could partially be attributed to the fact that advancement in age reduces the physical energy for rigorous farming activities especially in Ghana where farming involves the use of man-power. The significant positive effect of the age of farmers is contrary to the study by Demissie and Legesse (2013) on rural households in Ethiopia who reported a negative and significant effect on off-farm participation. Similarly, farmers with longer years of experience in maize farming allocate part of their time to off-farm activities as indicated by the 10% significance level of farm experience variable. Educational attainment has a positive and significant effect on off-farm participation at 5% significant level which is in line with our *a priori* expectation. Higher educational achievement of rural household makes them more reluctant to participate in farming activities because a greater standard of education presents them with better opportunities elsewhere. These results support the findings of Owusu et al. (2011) and McCarthy and Sun (2009) in rural Northern Ghana.

Table 1: Estimates of the logistic regression model

Variable	Coefficient	Standard Error	P-values
Gender	0.41362	0.63643	0.566
Age of the farmer	0.25872	0.15399	0.023**
Age of the farmer squared	1.01860	0.00798	0.019**
Farm experience	1.49720	0.31987	0.059*
Educational attainment	0.58969	0.13836	0.024**
Farm labour	1.10826	0.12438	0.360
Farmer-based organization	0.98765	1.26889	0.992
Farm size	2.83553	0.86750	0.001***
Previous year's output	0.46192	0.09413	0.000***
Constant	3.21E+10	3.23E+11	0.016
Sample size	120		
Pseudo R2	0.7369		

******, **, * represent 1%, 5% and 10% significance level respectively.***

The coefficient of farm size exerts a significant positive effect at 1% level of significance. This result is contrary to the theoretical expectation that increase in farm size encourages farmers to increase output and income and consequently discourages off-farm participation. However, it is in line with the report documented by Nasir (2014) who used ordered probit regression model to determine factors contributing to off-farm participation in Ethiopia. The negative effect of farm size on off-farm participation, however, is reported by Babatunde et al. (2010). This outcome could partly be attributed to the fact that farmers with larger farm sizes get more crop income to diversify into other income generating activities to serve as an insurance against crop failure. Furthermore, the value of previous maize output had a positive and significant effect on off-farm participation. Higher output translates into higher income which may push the farmer into other off-farm income generating activities as a source of insurance against agricultural production and marketing risk. However, higher farm income from the previous season means the household may not need to go into off-farm activities. The positive effect of previous output on off-farm participation is consistent with the findings of Tasie et al. (2012).

Empirical estimation of the stochastic frontier model Results of hypotheses tests

Table 2 presents the results of the hypotheses tests. The test statistic of the functional form with its corresponding *P-value* shows that the decision to use Cobb-Douglas functional form was rejected in favour of the translog frontier function. The result of this hypothesis suggests that the translog specification was a more accurate representation of the data, given the frontier assumptions. The second hypothesis test indicated that the socio-economic variables in the inefficiency model do not explain the variation in the inefficiency term (u_i).

Table 2: Test of null hypotheses in the stochastic production for maize farmers

Hypotheses	Test statistic	P-value	Decision rule
Functional form test	29	0.00	Reject H_0: Translog is appropriate
Inefficiency effects are stochastic	15.89	0.00	Reject H_0: Presence of inefficiency
Effects of off-farm activities	13.64	0.00	Reject H_0: Off-farm activities exert significant effect

This hypothesis was also rejected in favour of the fact that at least one of the socio-economic variables included in the inefficiency model determine the inefficiency term (u_i). The final hypothesis states that the probability of maize farm households participating in off-farm activities has no influence on farm technical efficiency level. This null hypothesis was also rejected in favour of the alternate that engagement in off-farm activities explains the variation in farmers' technical efficiency levels.

The Determinants of maize output

The results of the maximum likelihood estimation of the stochastic frontier model are presented in Table 3. The values of the explanatory variables included in the transcendental production frontier were mean-corrected so that their averages were zero. The mean correction was to allow the first-order coefficient of the explanatory variables to be inferred as the output elasticities. Moreover, while the squared variables in the translog model show the effect of continuous use of that variable on maize production, the interaction terms indicate a complementarity or substitutability of the inputs employed on the maize farm. A significant positive coefficient of interaction term means the two factors are complements while a significant negative term means the two factors are substitutes.

Table 3: Maximum-likelihood estimates for parameters of the translog stochastic frontier production function for maize farmers in the study area

Variable	Parameter	Coefficient	Standard error
constant	β_0	0.89836[a]	0.02809
Farm Size	β_1	0.20159[b]	0.08226
Fertilizer	β_2	0.57994[a]	0.08452
Herbicides	β_3	-0.02807	0.06628
Family Labour	β_4	0.50076[a]	0.18724
Hired Labour	β_5	-0.59523[a]	0.20937
(Farm size)(Farm size)	β_{11}	0.63204[b]	0.3066
(Fertilizer)(Fertilizer)	β_{22}	0.3575	0.25121
(Herbicides)(Herbicides)	β_{33}	0.29482	0.25434
(Family Labour)(Family Labour)	β_{44}	0.38169	1.18252
(Hired Labour)(Hired Labour)	β_{55}	2.04394	1.46284
(Farm Size)(Fertilizer)	β_{12}	-0.92384[c]	0.50185
(Farm size)(Herbicides)	β_{13}	-0.73417[b]	0.35628
(Farm size)(Farm labour)	β_{14}	1.31132	0.923687
(Farm size)(Hired Labour)	β_{15}	-1.46426	1.05721
(Fertilizer)(Herbicides)	β_{23}	0.34132	0.40526
(Fertilizer)(Family Labour)	β_{24}	0.38794	0.82404
(Fertilizer)(Hired Labour)	β_{25}	0.01152	0.82571
(Herbicides)(Family Labour)	β_{34}	0.2697	0.69997
(Herbicides)(Hired Labour)	β_{35}	0.00413	0.99839
(Family Labour)(Hired Labour)	β_{45}	-2.326	2.50693
Sigma Squared	σ^2	0.027	
lambda	λ	0.128	

a, b and c denote 1%, 5%, and 10% level of significance.

A significant positive coefficient of interaction term means the two factors are complements while a significant negative term means the two factors are substitutes.

The results indicate that farm size, the quantity of fertilizer and family labour exert positive and significant effects on the maize output. The positive effects of farm size and fertilizer are in line with the findings from a similar study by Ogundari (2013). The quantity of hired labour exerts a significant negative effect on output, indicating that larger amounts of hired labour reduce the level of maize production. That is, to say, a high cost of labour reduces the amount that a farmer wishes to retain for his or her farming activities which will consequently reduce the expected quantity of output. Moreover, "farm size squared" was positive and statistically significant at 5% indicating that the continuous use of land increases output, all other things being equal. However, the interactions terms between "farm size and fertilizer" and "farm size and herbicides" were negative and statistically significant at 10% and 5%, respectively indicating substitutability of the inputs, meaning that to increase output if farm size is increased, then fertilizer or herbicides application must be reduced.

Input elasticities

Computing the input elasticity was important to determine the level of responsiveness of the various inputs to the mean output of maize. The estimated elasticities from the translog production function of mean maize output with respect to the inputs are reported in Table 4. The table indicates that farm size, the quantity of fertilizer, the quantity of herbicides, the supply of family labour and hired labour at their mean values were; 0.202, 0.580, -0.028, 0.501, and -0.595, respectively. The results suggest that, if land allocated to maize farming, with the right quantities of fertilizer and family labour were to be individually increased by 100%, then the mean output of maize is estimated to increase by 20%, 58%, and 50%, respectively.

Table 4: Elasticities of the mean maize output in the translog production frontier

Variable	Coefficient	Standard error
Farm size	0.20159	0.08226
Fertilizer	0.57994	0.08452
Herbicides	-0.02807	0.06628
Family labour	0.50076	0.18724
Hired labour	-0.59523	0.20937
Return-to-scale	0.659	

On the other hand, if the required quantities of herbicides and hired labour employed were to be individually increased by 100%, then the mean output of maize is estimated to decrease by about 2% and 60%, respectively. The expected decline in output as a result of an increase in hired labour and herbicides could partially be attributed to high cost of herbicides and labour in the study area. Moreover, the estimated returns-to-scale was 0.659 implying that maize production in the study area exhibited decreasing returns-to- scale. The decreasing returns-to-scale means that when all inputs included in the model are increased by 100%, the mean output of maize is estimated to increase by 65.9%. Thus, the proportionate increase in the input levels results in a less than proportional increase in output. This outcome may partly be attributed to poor management and agronomic practices. Similar findings were obtained by Ogundari (2013) and Solis et al. (2009).

Effects of off-farm participation on technical efficiency

In this study, the effects of farm households' participation in off-farm activities on technical efficiency were estimated by including the predicted, rather than the actual values of off-farm participation as an additional regressor in the technical inefficiency model. Table 5 provides the empirical results of the estimates of the determinants of technical efficiency. The Table reveals that the predicted technical efficiency varies considerably ranging from 31.5% to 99.8% with an average technical efficiency of approximately 90.7%, indicating that less than 10% of output is lost through inefficiency. This result could be ascribed to farmers' scale of operations and mismanagement of farming practices, among others. However, the average technical efficiency score of 90.7% obtained in the study is high compared to other studies. Fasasi (2007), Harmozia et al. (2012), Begum et al. (2016), and Awonyinka et al. (2009) reported an average technical efficiency score of 70%, 67%, 65%, and 52%, respectively.

Table 5: Determinants of technical inefficiency of maize farmers in Ghana

Variable	Coefficient	Standard error	P-value
Predicted off-farm income scores	6.23660	2.49160	0.012**
Educational attainment	-0.27445	0.1316	0.037**
Age of farmer	-15.4795	5.27597	0.003***
Distance to farm	6.65131	2.66041	0.012**
FBO membership	-0.0709	0.64593	0.913
Minimum TE	0.315		
Mean TE	0.907		
Maximum TE	0.998		

****** and ** denote significance level at 1% and 5%, respectively.***

Table 6: Mean technical efficiencies of participants and non-participants of off-farm income activities.

Parameter	Observation	Mean	Standard error
Participants of off-farm income	59	0.671	0.0283
Non-participants of off-farm income	61	0.867	0.02284
Mean difference		- 0.415	0.0338***

****** represent significant at 1% level***

The results also show that off-farm participation had a positive and significant effect on technical inefficiency. That is, the participation in off-farm activities reduces the technical efficiency levels of farmers. This result conforms to the results in Table 6 indicating that the estimated mean technical efficiency among the sub-sample of off-farm income participants and non-participants are 67.14% and 86.73%, respectively. Thus, engagement in off-farm income by maize farmers in the study area reduces their technical efficiency level by about 20%. The loss of productivity gains resulting from participation in off-farm income may be due to a reduction in quality of time allocated to farm management. Similarly, Diiro (2012) reported a negative influence of off-farm income participation on technical efficiency of maize production in Uganda. The result also agrees with the one obtained by Addai et al. (2014) who found that off-farm income has a positive correlation with the technical inefficiency of farmers. However, it contradicts the results of the study by Shittu (2014) who reported a significant positive effect of off-farm labour supply on technical efficiency of rural farm households in South-west Nigeria.

However, educational attainment and age of the farmer positively and significantly affect the technical efficiency of maize production in the study area. That is, farmers' level of education and age tend to increase their technical efficiency level. Education enhances farmer's ability to acquire technical knowledge, which consequently pushes them closer to the frontier output. The positive influence of age suggests that older farmers are more technically efficient than younger farmers. This may be due to farming experience and excellent managerial skills, which older farmers have acquired over time. The positive estimated coefficient of the variable 'distance to farm' suggests that farmers who have to walk a long distance to their farms might be tired before they start work, after walking for a long time. Again, walking for a long time also means that quality time for work on the farm is reduced which further reduces the level of efficiency. This may further reduce the amount of quality time allocated to farming activities at a given time, hence, reduces farmers' level of technical efficiency.

CONCLUSIONS

The study had identified the determinants of off-farm participation and its effects on the technical efficiency of maize production in the Tolon district of the northern region, Ghana. The main finding that farmers with no off-farm participation were more technically efficient than farmers with off-farm participation suggests that engagement in off-farm economic activities may undermine maize productivity gains. This is because off-farm opportunities are in competition with farm activities from the same household labour and other resources. Thus, farm-level policy measures directed towards making the agricultural sector attractive by promoting investment and employment opportunities in the rural areas so as to boost farmers commitment to farming activities is highly recommended. This may make farmers allocate more time to their farm management thereby increasing productivity levels. Moreover, to help policy makers introduce better target agricultural systems; there is a need for better understanding of what determines the participation of off-farm income and its effects on productivity. The study, therefore, recommends that research of such nature should be replicated in other areas of the country to get more knowledge about the issue of off-farm income and agricultural productivity.

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