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The effect of the adoption of yam minisett technology on the technical efficiency of yam farmers in the forest-savanna transition zone of Ghana

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Abstract

This paper uses cross-sectional data collected from 375 smallholder yam farmers in Ghana in 2010 to examine whether the adoption of yam minisett technology had an effect on the technical efficiency of production of the yam farmers. We correct for endogeneity in adoption and employ stochastic frontier analysis to investigate the effect of adoption of the technology on the technical efficiency of production. Our analysis suggests average technical efficiencies of 85.4% and 89.2% in the Ashanti and Brong Ahafo regions respectively. In addition, the effect of adoption of the technology on the technical efficiency of smallholder farmers was positive and significant in the Ashanti region, but negative in the Brong Ahafo region. Our results provide information to improve the uptake of production technologies and their effect on smallholder yam farmers in Ghana.

Keywords: yam; minisett technology; technical efficiency; Ghana

1. Introduction

Yam production is one of the main agricultural activities in West Africa, and the region contributes between 90% and 95% of world production (FAO 2010). In Ghana, yam is the most important food crop in terms of output value. It contributes about 17% of agricultural gross domestic product and also plays a key role in guaranteeing household food security (Kenyon & Fowler 2000). The crop occupies about 12% of the total cropped area of Ghana and the annual production was estimated to be 5.7 million metric tons in 2009 (Ministry of Food and Agriculture 2010). The importance of the crop is not only to the domestic market, as international customers also desire the sweeter taste of the well-known "Ghana yam". Ghana is currently the leading exporter of yam, contributing about 36% of world exports. The yam sector in Ghana is definitely important for household and national income as well as food security.

The potential of yam to contribute to national development is challenged by the use of traditional technologies. Among the numerous consequences are seasonal shortages and the high cost of seed yam. Efforts to ensure the sustainable availability of adequate seed yam include the introduction of the yam minisett technology by the International Institute of Tropical Agriculture (based in Nigeria) in collaboration with the Crops Research Institute of Ghana (Asante *et al.* 2011). The technology has also been promoted by the Roots and Tuber Improvement and Marketing Programme (RTIMP), funded by the International Fund for Agricultural Development and the Government of Ghana, and the West Africa Agricultural Productivity Programme (WAAPP) in Ghana.

The yam minisett technology was developed to minimise the use of over 30% of harvested tubers as seed. The technology is expected to contribute to the reduction of the cost of planting materials, which accounts for between 33% and 50% of the total production cost (Kambaska *et al.* 2009). Feedback on the performance of the yam minisett technology has not been documented since its introduction in Ghana (Wiredu *et al.* 2012). The success of the technology depends on its adoption by the targeted beneficiaries. However, besides vagaries in natural situations, such adoption decisions and the technology's intensity of use are influenced by institutional, psychological and socioeconomic factors (Diagne & Demont 2007; Wiredu *et al.* 2012).

Information on these factors is useful in promoting improved agricultural technologies. To maximise the adoption and impact of the yam minisett technology, this study identifies factors influencing the adoption or non-adoption of the minisett technology for producing seed yams. Existing literature on the yam industry in Ghana has focused largely on the nutrition, agronomy and marketing of the yams, but few studies address the issue of adoption of the minisett technology (Kenyon & Fowler 2000; Kambaska *et al.* 2009; Asante *et al.* 2011; Wiredu *et al.* 2012). In this paper, we extend the analysis of technical efficiency (TE) by taking into account the effect of adoption of the yam minisett technology among small-scale yam farmers in the forest transition agro-ecological zone of Ghana, which is the main area of major yam production in the southern and middle belts of the country.

2. Yam production and productivity growth in Ghana

Yam productivity growth in Ghana reflects in the country's ability to feed an ever-increasing population despite the constraints on yam production. Understanding the magnitude, direction and sources of yam productivity growth over the years can provide useful insights into how to increase yam production and, accordingly, to mitigate food insecurity and poverty in Ghana.

Table 1 shows the growth rates of yam production, area harvested and yield over the past four decades (1970 to 2010). With the exception of the 1990s, the performances of all the other years are not encouraging, with the 1970s having recorded negative performance. Area underproduction has been a major contributor to output growth over the 40-year period. In the 1970s, 1990s and 2000s, over 60% of growth in output was accounted for by increases in the area harvested. Only in the 1980s did contributions to output by yield (48%) almost equal that of area (50%).

Table 1: Production, area harvested and annual growth rates in yield and sources of output growth

Decade	Annual growth rate (%)			Contributions to output growth (%)		Major interventions in yam production
	Output	Yield	Area	Yield	Area	
1970-1980	-2.2	1.1	-3.5	-52	152	Insect pest management
1980-1990	6.5	3.1	4.4	48	52	Introduction of new varieties
1990-2000	24.2	7.4	16.8	31	69	Improved planting materials Provision of input credit Farmer field schools Training of agricultural extension staff Improved storage facilities Minisett technology
2000-2010	6.2	2.1	4.1	34	66	Improved planting materials Provision of input credit Training of certified seed growers training of agricultural extension staff Rapid training in minisett technology Ridging

Source: Ministry of Food and Agriculture (2010)

Intervention by the Roots and Tuber Improvement Programme (the RTIMP) and the WAAPP triggered spontaneous growth in yam output in the 1990s and 2000s, at a rate of 24.2%. This rate was largely due to interventions such as the introduction of improved planting materials, the establishment of farmer field schools, the training of certified seed growers and extension staff, alongside the introduction of the minisett technology (Ministry of Food and Agriculture 2010). Area harvested accounted for about 69% of the annual growth in yam production during the period. Until the late 1990s, research on root and tuber crops generally focused on cassava rather than yams (Kenyon & Fowler 2000). A limited number of research publications were available on roots and tubers, while yam research stagnated during the 1970s and 1980s. Hence there were few or no major interventions to yield significant improvement in output growth during this period (Table 1).

Regardless of the limited funding, the research systems established during that time had some success in identifying and developing improved varieties of root and tuber crops. However, due to inadequate extension advice, most technologies used by the yam farmers remained largely traditional, hence the impact of research on production “appears not to have been great” (Anon, 1994). This resulted in a negative annual growth rate in output during the 1970s.

Literature on the efficiency and productivity of yam production in Ghana is limited, with most of it concentrating mainly on maize, rice and cocoa (Agyei-Holmes *et al.* 2011; Wiredu *et al.* 2012). These studies have focused on the estimation of TE using restricted functional forms to examine factors that explain why some farmers are more efficient than others. The extent to which technology adoption affects the TE and productivity of farmers remains a matter of great interest. This will provide useful feedback to research, policy makers and development partners. This paper estimates the effect of adoption of the yam minisett technology on the TE of yam-producing households in the Ashanti and Brong Ahafo regions of Ghana.

3. Methodology

3.1 Study area

The study was conducted using cross-sectional data collected on the production of yam on farms in the forest-savannah transition agro-ecological zone in Ghana. This agro-ecological zone is located in the middle belt of the country, between latitudes 7°36’N and 8°45’N and longitudes 1°5’W and 2°1’E. This agro-ecological zone was selected because it is one of the major yam-producing areas in the country. The greatest part of the zone is in the Brong Ahafo region and extends to the Ashanti region. Yam is one of the most important food security and cash crops in this part of the country, and the biggest yam market in the country is located in this zone. Indeed, yam is the only crop that is celebrated annually by the inhabitants of this area.

3.2 Sampling technique and data

Multi-stage sampling was employed in this study. First, the forest-savannah transition agro-ecological zone was selected. Five major yam-producing districts in this zone – the Kintampo North and South Districts, the Nkoranza District and the Atebubu/Amantin District of the Brong Ahafo region, and the Ejura-Sekyedumasi District of the Ashanti region – were purposively selected. For each district, five to ten households were selected randomly from ten randomly sampled communities. Although the study intended to obtain a sample of 400, a total of only 375 yam farmers were involved due to discrepancies such as nonresponse and irrelevant data.

3.3 Empirical framework

In estimating the impact of the adoption of a technology or intervention on TE, the traditional approach involves a two-stage estimation procedure in which the probability of adoption is estimated using the probit or logit models and then used to obtain matched samples for each of the groups (adopters and non-adopters). In the second stage, the matched samples are used to estimate separate stochastic frontier models for each of the groups and the impact is assessed by the mean difference in TE between the beneficiaries and non-beneficiaries. A drawback of this approach is its inability to take into account the selection bias associated with observed and unobserved variables. In addition, our analysis could not apply this method because of data limitations.

A second approach is similar to the first one: after estimating the probability of adoption, the matched samples are used to estimate a single stochastic frontier model and the resulting TE scores. The mean difference in the TEs of adopters and non-adopters or beneficiaries and non-beneficiaries is used to assess the impact (Mouelhi 2009; Oduol *et al.* 2011).

A third and recent approach, proposed by Greene (2010), involves a simultaneous estimation of both the matched samples and a single stochastic frontier model. This approach takes into account both observed and unobserved biases by jointly estimating the probit, the propensity scores as well as the TE scores (Solís *et al.* 2009; Bravo-Ureta *et al.* 2011).

To estimate the impact of the adoption of the yam minisett technology on TE, we follow Oduol *et al.* (2011) and model adoption as a choice variable and estimate the determinants of adoption. We estimate the predicted probabilities of adoption and regress these together with other household, farm-level and institutional covariates in the stochastic frontier inefficiency model. This approach corrects for endogeneity in adoption before incorporating it into the TE estimation.

The adoption model is explicitly expressed as:

$$T_{Ai} = \alpha_0 + \sum_{k=1}^{6} \alpha_{Hk} H_{ki} + \sum_{k=1}^{2} \alpha_{Gk} G_{ki} + \sum_{k=1}^{3} \alpha_{Yk} E_{ki} + e_i \qquad (1)$$

where α_{Hk}, $\alpha_{X,k}$ and $\alpha_{Y,k}$ are parameters of the *H, GX* and *E* variables respectively; H_1 denotes the age of the household head; H_2 denotes the gender of the household head; H_3 denotes the number of years of formal education of the household head; H_4 denotes the years of experience of the household head in yam cultivation; H_5 denotes whether the yam farmer is a native[1] or not; and H_6 denotes access to extension services; G_1 represents farm size used for yam production; G_2 is the number of people days of family labour used for yam production; E_1 is the perception about the cost of the minisett technique; E_2 is the ease of adoption and use of minisett; E_3 is the expectation of more seed yams from the minisett technique; and e_i is the random error term in the probit model.

With the assumption of interactions between the factors affecting both adoption and impact, the second stage involves the estimation of the stochastic frontier production function, which includes the predicted probability of adoption of the yam minisett technology.

We used the transcendental logarithmic (translog) production function developed by Christensen *et al.* (1973) to define the relationship between output and inputs. A Cobb-Douglas functional form was also considered for representing the production model. However, a preliminary test of hypothesis suggested that the Cobb-Douglas is not an adequate representation of the data, given the assumptions of the translog stochastic frontier model.

Following Battese and Coelli (1995), the translog stochastic frontier model is defined by:

$$\ln Y_i = \beta_0 + \sum_{j=1}^{2} \beta_{0j} D_{ji} + \sum_{j=1}^{5} \beta_j \ln X_{ji} + 0.5 \sum_{j \le k=1}^{5} \sum^{5} \beta_{jk} \ln X_{ji} \ln X_{ki} + V_i - U_i \tag{2}$$

where the subscript i indicates the i^{th} farmer in the sample (i = 1, 2, …, N = 375);
Y represents the quantity of yam harvested for the sampled farmer (number of tubers[2]);
D_1 is the dummy variable that has a value of 1 if the farmer is a member of a farmer-based organisation (FBO), and 0 otherwise (*FBO dummy*);
D_2 is the dummy variable that has a value of 1 if the farmer has some minisett training, and 0 otherwise (*Training dummy*);
X_1 is the total area of *land* (in hectares) planted to yam (*Land*);
X_2 is the total labour (in people days) used in yam cultivation (*Labour*);
X_3 is the number of stakes used in production (*Stakes*);
X_4 is the number of seed yams used in planting (*Seed*);
X_5 is the predicted probability of adoption of minisett technology (*Adoption)*;
the $V_i s$ are random errors that are assumed to be independently and identically distributed as $N(0,\sigma^2_V)$ random variables; the $U_i s$ are the non-negative technical inefficiency effects that are assumed to be independently distributed among themselves and between the $V_i s$, such that U_i is defined by the truncation (at zero) of the $N(\mu_i, \sigma^2)$ distribution, where μ_i is defined by:

$$\mu_i = \delta_0 + \sum_{j=1}^{2} \delta_{0j} D_{0ji} + \sum_{j=1}^{6} \delta_j Z_{ji} \tag{3}$$

where D_{01} is the minisett adoption dummy variable (*Adoption dummy*);
D_{02} is the *Training dummy* variable ($D_{02} = D_2$, as defined above);
Z_1 represents the logarithm of Land ($Z_1 \equiv \log(X_1)$);
Z_2 represents age of the household head (in years) (*Age*);
Z_3 represents the household size (number) (*Size*);
Z_4 represents the years of formal education of the household head (*Education*[3]);
Z_5 represents the years of experience in yam cultivation (*Experience*[4]); and

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[1] *Native* here refers to a farmer who hails from the community where he or she cultivates yam.

[2] Farmers in this region only count the number of tubers, rather than weigh them. The tubers are relatively uniform in size, hence "number of tubers" is a reasonable measure.

[3] Z_4 is the same as H_3, as defined in Equation (1).

[4] Z_5 is the same as H_4 as defined in Equation (1).

Z_6 represents the total income from farming (in Cedis) (*Income*).

The variation in output levels depends largely on the quantity of inputs used in production, while differences in technical inefficiencies are explained by productivity-enhancing factors. The dependent variable in the production function (2) is the total number of tubers of yams harvested. The explanatory variables included in the frontier production function comprise area of land under yam, number of stakes used in production, quantity of seed, labour used in the production operations, participation in training in the minisett technology and FBO membership. *Stakes* refers to sticks used to direct and hold up the stem of the yam plant to enhance its exposure to sunlight, eventually improving on the photosynthetic processes and yield. Generally, not all farmers are able to obtain enough stakes for their yam farms due to the cost involved. Hence, all things being equal, staked yams are expected to have higher yields than non-staked ones. Different sources of labour, as hired, family or exchanged, are all quantified in terms of people days per year. These variables are important physical inputs used in yam production. The predicted probability of adoption variable is also included in the production function to assess the impact of adoption on the productivity of the farmers in yam production. This is to ensure that adopters are matched on the basis of this probability of adoption to non-adopters.[5]

Besides describing the relationship between inputs and yam output, we are also concerned with those factors that influence farmers' technical inefficiency in their decision making. The model for the technical inefficiency effects contains variables associated with human capital, such as experience in major yam cultivation, amount of schooling and the age of the head of the household. The variables other than predicted adoption of minisett technology have been used in models for the technical inefficiency effects in several previous studies, including Battese and Broca (1997), Villano and Fleming (2006) and Murova and Chidmi (2013).

The TE of the *i*th farmer is defined by

$$TE_i = e^{-U_i} \tag{4}$$

where the distribution of the U_is is defined by the specifications of the inefficiency model in Equation (3). The prediction of the technical efficiencies is based on the conditional expectation, given the unobservable composed error, V_i - U_i (see Jondrow *et al.* 1982 and Battese & Coelli 1988).

3.4 Empirical analysis

In the technical inefficiency model of Equation (3) we control for variations in technical inefficiency that are attributable to differences in socio-economic, bio-physical and institutional factors. In our stochastic frontier model, the major focus is on the effect of adoption of yam minisett technology on productivity. Consequently, we use most of the household covariates used in the adoption model.

The parameters of the stochastic frontier production function model, defined by Equations (2) and (3), are jointly estimated by the maximum-likelihood method using the program FRONTIER 4.1 (Coelli 1996).

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[5] A more traditional modelling approach would be to define two stochastic frontier models for adopters and non-adopters of the yam minisett technology and test if they were the same model. However, this approach does not account for the stochastic element in yam farmers deciding to adopt the minisett technology.

Tests of several null hypotheses for the parameters in the frontier production function and in the inefficiency model were performed using the generalised likelihood-ratio test statistic defined by

$$\lambda = -2\{\ln[L(H_0)/L(H_1)]\} \tag{5}$$

where $L(H_0)$ and $L(H_1)$ denote the values of the likelihood function under the null (H_0) and alternative (H_1) hypotheses respectively. If the null hypothesis is true, the test statistic has approximately a chi-squared or a mixed chi-squared distribution, with degrees of freedom equal to the difference between the numbers of the parameters involved in the alternative and null hypotheses. If the inefficiency effects are absent from the model, as specified by the null hypothesis, $H_0 : \delta_0 = \delta_{01} = \delta_{02} = \delta_1 = ... = \delta_6 = \gamma = 0$, where $\gamma = \sigma^2 / \sigma_S^2$ and $\sigma_S^2 = \sigma_V^2 + \sigma^2$, then λ is approximately distributed according to a mixed chi-squared distribution with at least 10 degrees of freedom. In this case, critical values for the generalised likelihood ratio test are obtained from Table 1 of Kodde and Palm (1986).

In the preliminary analyses, the null hypotheses that were tested were that the frontier models for both regions were the same and also that the frontier models were the same except that the intercept parameters may be different. These hypotheses were strongly rejected. In view of this, separate frontier models for the two regions were desirable and their parameters were estimated in our study.

4. Results and discussion

4.1 Characteristics of the sample households

Table 2 presents descriptive statistics of the sample households. Overall, about 58% of the farmers had adopted and were using the minisett technology. On average, household heads were about 41 years old and 86% of them were male. About 37% of the farmers were natives of the communities in which they resided. On average, household heads had about 4.5 years of formal education. The typical household comprises an average of over eight persons, and the average years of yam cultivation were about 19. The number of extension contacts was higher among yam farmers in the Brong Ahafo than in the Ashanti region. On average, more than 50% of the farmers had training in minisett technology. About 60% of the farmers were members of an FBO. The data on technology attributes suggest that most of the households had high expectations of the returns accruing from adopting the minisett technology. For instance, about 60% of the farmers perceived the technology to be less expensive and easy to adopt. About half of the farmers believed that the technique would produce more seed yams than the conventional method.

4.2 Empirical results

The maximum-likelihood estimates of the parameters of the probit model are presented in Table 3. The results suggest that, except for age, education, being a native of the community, extension contacts, household size, ease of adoption and perception of obtaining more seed yams from the technique, all other variables were not significant at the 10% level. However, all these variables had a positive effect on adoption of yam minisett technology (Table 3).

The positive effect of the age variable suggests that older farmers are more likely to adopt the technology. Because yam cultivation exploits the soil nutrients to a great extent, farmers usually move to new land after each season. In view of this, access to land is vital to yam production. Being a native of the community offers farmers enhanced access to land, thus having a positive influence on adoption decisions. The estimated marginal effects revealed that being a native increases the probability of adoption by 6.03%.

The farmers' perceptions of the ease of adopting the technology had a positive effect on adoption and was highly significant. This is not surprising, because the farmers' perceptions of technology attributes are more likely to influence adoption decisions. The major constraint in yam production in Ghana is access to viable seed yams (Ministry of Food and Agriculture 2010); hence, positive influence of the perception variables was expected

Table 2: Descriptive statistics of yam farmers in the Ashanti and Brong Ahafo regions[*]

Variables	Ashanti (N = 103)	Brong Ahafo (N = 272)	Overall (N = 375)
Adoption	0.78 (0.28)	0.51 (0.26)	0.580 (0.27)
Age (years)	38.4 (15.2)	42.3 (15.4)	41.3 (15.4)
Gender	0.79	0.89	0.86
Education (years)	6.0 (4.5)	3.9 (4.7)	4.5 (4.7)
Experience	17.6 (15.1)	19.6 (13.5)	19.1 (14.0)
Demonstration visits	0.67	0.53	0.57
Land (acres)	6.3 (4.2)	4.9 (3.9)	5.3 (4.1)
Labour (people days)	126 (88)	96 (79)	104 (82)
Nativity	0.24	0.42	0.37
Household size (N)	8.3 (3.8)	8.7 (5.1)	8.6 (4.8)
Yield (number of tubers)	8 684 (9 541)	6 151 (9 610)	6 847 (9 646)
Seed	6 427 (5 217)	5 026 (4 542)	5 411 (4 771)
Seed price/100 (GHC)	113.6 (72.2)	146.0 (193.4)	137.1 (169.5)
Income (GHC)	992.3 (451.9)	969.9 (802.3)	976.1 (722.6)
Stakes	317 (193)	305 (209)	308 (205)
Perception about cost	0.45	0.64	0.59
Easy to adopt	0.65	0.66	0.66
Expects more seed yams	0.41	0.61	0.55
Extension contacts per year	1.8 (2.7)	8.0 (10.2)	6.3 (9.2)
FBO membership	0.59	0.61	0.61

[*]Figures in parentheses are standard deviations.

Table 3: Maximum-likelihood estimates for parameters of the probit model[6] for yam farmers in the Ashanti and Brong Ahafo regions

Variable	Coefficient	Marginal effects	SE[7]	*p*-value
Constant	-2.991	-2.333	0.45	0.0000
Age	0.027	0.010	0.0021	0.0000
Gender	-0.174	-0.063	0.088	0.4690
Education	0.046	0.017	0.0064	0.0060
Experience	0.001	0.000	0.0023	0.8510
Nativity	0.469	0.169	0.060	0.0050
Extension	0.033	0.012	0.0041	0.0020
Land	-0.055	-0.020	0.027	0.4570
Labour	0.013	0.005	0.0014	0.0010
Perception about cost	0.156	0.058	0.065	0.3690
Easy to adopt	0.559	0.212	0.067	0.0010
More seed yams	0.467	0.174	0.062	0.0040

As expected, educated farmers have greater ability to process information and search for technologies suitable to addressing their production constraints. The estimated marginal effect of this variable indicated that the probability of adopting the technology increases by 0.64% for an additional year of formal education.

The maximum-likelihood estimates of the parameters of the translog stochastic frontier production functions of the two regions are presented in Table 4. The maximum-likelihood estimates of the

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[6] A single model was estimated for both regions and used to obtain the predicted adoption scores before separating the scores to be included in the stochastic frontier models to estimate the technical efficiencies of the regions.

[7] Standard errors of estimators are given correct to two significant digits in this and subsequent tables.

parameters of the inefficiency models for the two regions are presented in Table 5. The values of the explanatory variables in the translog stochastic frontier model were mean-corrected by subtracting the means of the variables so that their averages were zero. This approach enables the first-order coefficients of the input variables to be interpreted as estimates of output elasticities for the individual inputs at the mean input values.

All estimated first-order coefficients in the production function fall between zero and one, except those for *Land* and *Labour* for the Ashanti region and *Seed* for the Brong Ahafo region. The negative estimates contradict the monotonicity condition that all marginal products are positive at the mean input levels. The results indicate that *Land* and *Stakes* have much greater impact on the production of yams in the Brong Ahafo than in the Ashanti region.

Furthermore, it was found that including the predicted adoption in both production functions had a positive effect on yam production, but was only significant in the Brong Ahafo region. *Labour* had a mixed effect in the two regions. It had a negative effect on yam output in the Ashanti region, but its effect was positive in the Brong Ahafo region.

The γ-parameter associated with the variance of the technical inefficiency effects in the stochastic frontiers was estimated to be very high for both the regions. These results indicate that the technical inefficiency effects are a significant component of the total variability of yam output in the regions.

Table 4: Maximum-likelihood estimates for parameters of the translog stochastic frontier production function for yam farmers in the Ashanti and Brong Ahafo regions

		Ashanti		Brong Ahafo	
Variable	**Parameter**	**Coefficient**	**SE**	**Coefficient**	**SE**
Constant	β_0	0.226	0.020	0.156	0.039
FBO Dummy	β_{01}	0.0147	0.0041	-0.033[a]	0.029
Training Dummy	β_{02}	-0.029[a]	0.018	-0.085[b]	0.035
Land	β_1	1.062	0.087	0.83	0.20
Labour	β_2	-0.532	0.096	0.19[a]	0.19
Stakes	β_3	0.426	0.016	0.778	0.051
Seed	β_4	0.118	0.041	-0.00[a]	0.13
Adoption scores	β_5	0.016[a]	0.019	0.117[b]	0.065
$(Land)^2$	β_{11}	-8.03	0.43	-0.86[a]	0.83
(*Land*)(*Labour*)	β_{12}	4.98	0.25	0.44[a]	0.62
(*Land*)(*Stakes*)	β_{13}	-1.63[c]	0.62	0.43[a]	0.66
(*Land*)(*Seed*)	β_{14}	1.991	0.071	0.91[b]	0.54
(*Land*)(*Adoption scores*)	β_{15}	0.61	0.12	0.75[a]	0.62
$(Labour)^2$	β_{22}	-2.25	0.38	0.62[a]	0.82
(*Labour*)(*Stakes*)	β_{23}	3.74	0.43	1.21[b]	0.75
(*Labour*)(*Seed*)	β_{24}	-1.62	0.39	-1.03[c]	0.47
(*Labour*)(*Adoption scores*)	β_{25}	-0.47[a]	0.31	0.09[a]	0.72
$(Stakes)^2$	β_{33}	0.16[a]	0.12	-0.15[a]	0.15
(*Stakes*)(*Seed*)	β_{34}	-1.08	0.13	-1.49	0.48
(*Stakes*)(*Adoption*)	β_{35}	-0.39[a]	0.20	0.12[a]	0.10
$(Seed)^2$	β_{44}	-0.366	0.025	0.10[a]	0.23
(*Seed*)(*Adoption*)	β_{45}	0.12[a]	0.21	-0.59[a]	0.52
$(Adoption)^2$	β_{55}	-0.100	0.019	-0.0097[a]	0.0062
Gamma	γ	0.999997	0.000083	0.904	0.033
Variance parameter	σ_S^2	0.1287	0.0081	0.265	0.083
Log likelihood function		106.063		53.79	

[a] significant at the 1% level, [b] significant at the 5% level, [c] significant at the 10% level.

The estimated coefficients of the inefficiency effects model for these two regions are presented in Table 5. *Land* (area planted to yam production), *Experience* in yam cultivation and *Training* (participation in minisett adoption training) had negative association with technical inefficiency in both regions. The negative effect of *Land* indicates that increasing the area under yams results in lower technical inefficiencies in yam production. This indicates that there are greater efficiencies of yam production on larger plots of land. Most of the increases in output over recent years have been as a result of increases in the area under yam cultivation.

Age had a positive association in both regions, indicating that older farmers tend to be more inefficient in yam production. For the Ashanti region, all of the explanatory variables for the inefficiency effects, except *Age* and *Income* from yam cultivation, had negative estimated coefficients. The negative sign for the minisett adoption dummy variable shows that farmers who adopted the technology tended to have smaller technical inefficiencies in yam production than non-adopters, all else being equal. The coefficient of *Education* had a negative sign, which implies that more educational training acquired by yam farmers was associated with lower technical inefficiency of yam production in the Ashanti region.

Table 5: Maximum-likelihood estimates for parameters of the inefficiency effects model of the translog stochastic frontier production functions for yam farmers in two regions of Ghana

		Ashanti		Brong Ahafo	
Variable	**Parameter**	**Coefficient**	**SE**	**Coefficient**	**SE**
Constant	δ_0	0.33[a]	0.34	-1.59[b]	0.85
Adoption dummy	δ_{01}	-0.07[a]	0.13	0.49[c]	0.22
Training dummy	δ_{02}	-1.26	0.16	-1.41	0.56
Land	δ_1	-0.039	0.011	-0.018[a]	0.018
Age	δ_2	0.0193	0.0041	0.0048[a]	0.0040
Household size	δ_3	-0.0753	0.0063	0.033[c]	0.016
Education	δ_4	-0.0513	0.0029	0.050[c]	0.022
Experience	δ_5	-0.00432	0.00096	-0.024[c]	0.012
Income	δ_6	0.00019[a]	0.00013	-0.000104[c]	0.000052

[a] significant at the 1% level, [b] significant at the 5% level, [c] significant at the 10% level.

For the Brong Ahafo region, the estimates for the inefficiency parameters suggest negative relationships between the technical inefficiencies of yam production and *Experience*, *Training*, *Land* and *Income*, but positive relationships between the technical inefficiencies of yam production and A*doption* of the minisett technology, *Age*, *Size* and *Education*. However, except for *Training*, all the other coefficients are significant at the 10% level. The positive sign for the minisett adoption dummy variable shows that farmers in the region who adopted the yam minisett technology have higher technical inefficiencies in yam production than non-adopters for given levels of the variables involved. The negative coefficient of *Income* suggests that higher levels of farm income are associated with lower levels of technical inefficiency. Income from farming activities plays an important role in technical inefficiency because yam production is generally capital intensive, thus higher farm incomes empower small-scale farmers to ensure sustainable yam production in the Brong Ahafo region.

Tests of hypotheses for the coefficients of the technical inefficiency effects are presented in Table 6. The first hypothesis tested is that there are no technical inefficiencies in the production function, $H_0: \delta_0 = \delta_{01} = \delta_{02} = \delta_1 = \ldots = \delta_6 = \gamma = 0$, where $\gamma = \sigma^2/(\sigma_V^2 + \sigma^2)$ is the ratio of the variance associated with inefficiency effects and its sum with the variance of the random errors in the production of yam. The results obtained indicate that the null hypothesis of no technical inefficiencies of yam production should be strongly rejected for both regions. This indicates that the traditional production function is not an adequate representation of the data, given the assumptions of the stochastic frontier model**.**

The second null hypothesis considered in Table 6 is $H_0: \delta_0 = \delta_{01} = \delta_{02} = \delta_1 = \ldots = \delta_6 = 0$, which indicates that all the coefficients of the explanatory variables in the inefficiency model are equal to zero (technical inefficiency effects have half-normal distribution). If this hypothesis is true, then the explanatory variables in the inefficiency model do not influence the technical inefficiencies of yam production. This null hypothesis is also rejected for both regions.

The third null hypothesis in Table 6, $H_0: \beta_{ij} = 0$ for all $i \le j = 1, 2, \ldots, 5$, states that the second-order coefficients in the translog production function have zero values and, if this hypothesis is true, then the Cobb-Douglas production function applies. For both regions, this null hypothesis is rejected, even if the level of significance for the test is as small as 5%.

Finally, the fourth null hypothesis, $H_0: \beta_5 = 0$, states that the probability of adopting the minisett technology has no effect on the productivity and efficiency of yam farmers. This null hypothesis is also rejected for both regions.

Table 6: Tests of null hypotheses for parameters in the stochastic frontier production function and the inefficiency effect models for yam farmers in Ghana

Null hypothesis	Ashanti			Brong Ahafo		
	λ	Critical value^a	Decision	λ	Critical value^a	Decision
$H_0: \delta_0 = \delta_{01} = \delta_{02} = \delta_1 = \ldots = \delta_6 = \gamma = 0$	156.3	17.67	Reject H_0	43.7	17.67	Reject H_0
$H_0: \delta_0 = \delta_{01} = \delta_{02} = \delta_1 = \ldots = \delta_6 = 0$	49.47	16.27	Reject H_0	19.63	16.27	Reject H_0
$H_0: \beta_{ij} = 0$ for all $i \leq j = 1, 2, \ldots, 5$	63.98	24.38	Reject H_0	30.97	24.38	Reject H_0
$H_0: \beta_5 = 0$	15.84	2.71	Reject H_0	39.65	2.71	Reject H_0

[a] Taken from Table 1 of Kodde and Palm (1986), using the 5% level of significance.

4.3 Elasticities of inputs

The estimates of the elasticities of output with respect to inputs of production are presented in Table 7. Because the variables of the translog model were mean-corrected to zero, the first-order coefficients are the estimates of elasticities at the mean input levels. For the translog model, the elasticities of mean yam output with respect to the different inputs depend on several parameters and values of the inputs. For a non-neutral stochastic frontier production function, the elasticity of mean yam output with respect to the j^{th} input variable is defined by the following expression (Battese & Broca 1997):

$$\frac{\partial \ln E(Y_i)}{\partial \ln X_{ji}} = \{\beta_j + \sum_{k=1}^{5} \beta_{jk} \ln X_{ki}\} - C_i \left(\frac{\partial \mu_i}{\partial \ln X_{ji}} \right) \tag{6}$$

where μ_i is defined in Equation (3); $C_i = 1 - \frac{1}{\sigma} \left\{ \frac{\phi\left(\frac{\mu_i}{\sigma} - \sigma\right)}{\Phi\left(\frac{\mu_i}{\sigma} - \sigma\right)} - \frac{\phi\left(\frac{\mu_i}{\sigma}\right)}{\Phi\left(\frac{\mu_i}{\sigma}\right)} \right\}$; and ϕ and Φ represent the density and distribution functions of the standard normal random variable respectively.

The first component of the elasticity of Equation (6) is called the *elasticity of frontier output* with respect to the j^{th} input variable. The second component is called the *elasticity of technical efficiency* with respect to the input involved. Only the *Land* input in the production function is also involved in the inefficiency model, so that, for the other inputs, the elasticity of TE is zero. However, for *Land*, the second component of Equation (6) is non-zero, hence it was calculated.

The empirical results show that, from the estimates of the translog production function models for the Ashanti region, the *frontier elasticity* of *Land* is estimated to be 1.062, but the total elasticity of land is estimated to be 0.17, with a standard error of 0.15 using the appropriate elements of the estimated covariance matrix for the maximum-likelihood estimates. The estimated elasticities of yam output with respect to *Labour, Stakes* and *Seed* are -0.532, 0.426, and 0.118 respectively, at the mean input values. This indicates that, if the number of *Stakes* and *Seed* yams were to be individually increased by 1%, then the mean production of yam is estimated to increase by 42.6% and 11.8% respectively. The negative estimated elasticity of labour in the Ashanti region merits further investigation.

For the Brong Ahafo region, the *frontier elasticity* of *Land* is estimated to be 0.83, but the total elasticity of land is estimated to be 0.97, with a standard error of 0.20 at mean input values. Further, the elasticity of *Labour* is estimated to be positive, but it is not highly significantly different from zero. The elasticity of mean yam output with respect to *Stakes* is quite large and highly significant at 0.778. The elasticity of *Seed* yams is estimated to be slightly negative but highly insignificant.

Table 7: Elasticities of mean yam output with respect to inputs in the stochastic frontier production functions

Input	Ashanti	Brong Ahafo
Land	0.17 (0.15)	0.97 (0.20)
Stakes	0.426 (0.016)	0.778 (0.051)
Seed	0.118 (0.041)	-0.00 (0.13)
Labour	-0.532 (0.096)	0.19 (0.19)

4.4 Technical efficiency indexes

Table 8 shows the distribution of the predicted technical efficiencies of the sample yam farmers in the Ashanti and Brong Ahafo regions. The average predicted technical efficiencies are not significantly different between the two regions (between 0.85 and 0.89), but the distributions are quite different. In the Ashanti region there are relatively more very inefficient yam farmers with technical efficiencies of less than 0.80 (27.2% of the sampled farmers). However, in the Brong Ahafo region there are only 6.0% of the sampled farmers with technical efficiencies of less than 0.80. On average, the yam farmers in the Ashanti region were producing yam at about 85% of the potential (stochastic) frontier production levels, given the technology currently being used. For the Brong Ahafo region, the yam farmers produced yam at about 89% of the potential frontier production levels. Thus, in the short run there is capacity for increasing yam production by 15% and 11% by adopting best practice yam production techniques in the two regions respectively.

Previous studies on efficiency and productivity using cross-sectional data have included socio-economic variables in the technical inefficiency model, such as formal education, age, household size, experience in cultivation, extension contacts, etc. (Villano & Fleming 2006; Chaovanapoonphol *et al.* 2009; Margono *et al.* 2011). For this study, the empirical results shows that *Experience* in yam production had a positive effect on the technical inefficiencies in both regions, but the effect was significant only in the Brong Ahafo region.

Table 8: Percentages of technical efficiencies of yam farmers in Ashanti and Brong Ahafo regions, within decile ranges

Interval	Ashanti	Brong Ahafo
< 0.5	6.8	1.5
0.51–0.60	5.8	0.4
0.61–0.70	9.7	1.5
0.71–0.80	4.9	2.6
0.81–0.90	7.8	33.5
0.91–1.00	65.0	60.7
Total	103	272
Mean	0.854	0.892
SD	0.181	0.082
Maximum	0.999	0.978
Minimum	0.277	0.292

In the present study, more than half of the farmers had a mean TE in the range of 0.91 to 0.99 in both regions. In the Ashanti region, 7.8% of the farmers had a mean TE in the range of 0.81 to 0.90. The remaining portion of the farmers had a mean TE ranging from 0.51 to 0.80. This means that most of the sampled yam farmers are technically efficient in the allocation and use of their inputs.

4.5 Effect of adoption of yam minisett technology on technical efficiency

The TEs of adopters versus non-adopters of the minisett technology are presented in Table 9. These results indicate that adoption of yam minisett technology had a positive significant effect on the TE of smallholder farmers in the Ashanti region, but a negative impact on smallholder farmers in the Brong Ahafo region. The estimated TEs among the sub-sample of adopters in the Ashanti and Brong Ahafo regions are 87% and 88% respectively. However, the estimated TE among the sub-sample of non-adopters is much higher in the Brong Ahafo region (91%) than in the Ashanti region (81%). Consequently, these results suggest that adoption of yam minisett technology is likely to increase TE by 5.4% in the Ashanti region and reduce it by 2.7% in the Brong Ahafo region. These findings are consistent with those of Mouelhi (2009), who found that the adoption of ICT increased TE significantly in the Tunisian manufacturing sector. Conversely, negative impacts of adoption among smallholder farmers have also been reported in Africa and Asia (Chaovanapoonphol *et al.* 2009; Oduol *et al.* 2011).

Table 9: Technical efficiencies of adopters versus non-adopters of yam minisett technology

Parameter	Ashanti	Brong Ahafo
Observations	103	272
Number of adopters	78	166
Mean TE of adopters	0.867(0.021)[a]	0.8817 (0.0072)[b]
Mean TE of non-adopters	0.813(0.035)[a]	0.9093 (0.0058)[b]

[a] significant at the 1% level, [b] significant at the 5% level, [c] significant at the 10% level
Standard errors are in parentheses

5. Conclusions and policy implications

The adoption of minisett technology was estimated at 78% and 51% in the Ashanti and Brong Ahafo regions respectively. The adoption process was influenced significantly by farmers' age, education, household size, being a native of the community, extension contacts, ease of adopting and expectation of obtaining more seed yams from the technique. For the Ashanti region, the estimated TE ranged from 27.7 to 99.9%, with a mean of 85.4%. However, it ranged between 29.2 and 97.8% in the Brong Ahafo region, with a mean of 89.2%. The results also suggest that the adoption of minisett technology is negatively and significantly associated with TE in the Brong Ahafo region, indicating that the benefits of adoption of minisett technology have not been translated into improved TE in that region. However, adoption of the minisett technology had a positive impact on TE in the Ashanti region.

The results highlight the importance of extension activities in technology adoption and their impact on farmers' performance. Continuous provision of training is thus recommended to enhance the smooth transformation of adoption efforts into efficient yam production. It can also be gleaned that enhancing access to extension services and programmes can be strengthened, possibly through the establishment of good practice centres in the districts. In the long run, an improvement in minisett technology to make it more cost effective by using locally available materials that are relatively cheap will go a long way to improving adoption and hence efficient production.

In this study the impact of technology adoption on TE was examined using a cross-sectional dataset. A panel dataset could be obtained by conducting a complementary survey that presents the adoption and impact variables over time, and this could allow for a more thorough analysis of the impact of the yam minisett technology on TE over time. Finally, the propensity score matching approach seeks to control for the observable covariates that are partly responsible for self-selection. In reality, however, self-selection may also be affected by some unobservable covariates, particularly in the case of adoption where the treatment is endogenous; there also is the possibility of noncompliance.

A joint estimation approach that takes into account both observed and unobserved biases by jointly estimating the adoption model is suggested for future analyses.

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References

Agyei-Holmes A, Osei-Akoto I & Asante BO, 2011. Cost structure of yam farmers in Ghana: The case of the forest savannah transition agro-ecological zone. Paper read at the first conference of the West Africa Agricultural Productivity Programme (WAAPP), 12–16 September, Accra, Ghana.

Anon, 1994. Ghana: National agricultural research strategic plan: Final report. Ministry of Food and Agriculture (MOFA), Accra, Ghana.

Asante BO, Otoo E, Wiredu AN, Acheampong P, Osei-Adu J & Nsiah-Frimpong B, 2011. Willingness to adopt the vine multiplication technique in seed yam production in the forest savannah transition agro-ecological zone, Ghana. Journal of Development and Agricultural Economics 3: 710–9.

Battese GE & Broca SS, 1997. Functional forms of stochastic frontier production functions and models for technical inefficiency effects: A comparative study for wheat farmers in Pakistan. Journal of Productivity Analysis 8: 395–414.

Battese GE & Coelli TJ, 1988. Prediction of firm-level technical efficiencies with a generalised frontier production function and panel data. Journal of Econometrics 38: 387–99.

Battese GE & Coelli TJ, 1995. A model for technical inefficiency effect in stochastic frontier production for panel data. Empirical Economics 20: 325–45.

Bravo-Ureta B, Almeida A, Solís D & Inestroza A, 2011. The economic impact of Marena's investment on sustainable agricultural systems in Honduras. Journal of Agricultural Economics 62: 429–48.

Chaovanapoonphol Y, Battese GE & Chang HS, 2009. The impact of agricultural loans on the technical efficiency of rice farmers in the Upper North of Thailand. In Lee J-D & Heshmati A (eds), Productivity, efficiency, and economic growth in the Asia-Pacific region. Berlin, Heidelberg: Springer-Verlag.

Christensen LR, Jorgenson DW & Lau LJ, 1973. Transcendental logarithmic production frontiers. Review of Economics and Statistics 55: 28–45.

Coelli TJ, 1996. A guide to FRONTIER version 4.1: A computer program for stochastic frontier production and cost function estimation. Centre for Efficiency and Productivity Analyses Working Papers, No. 7/96, Department of Econometrics, University of New England, Armidale.

Diagne A & Demont M, 2007. Taking a new look at empirical models of adoption: Average treatment effect estimation of adoption rate and its determinants. Agricultural Economics 37: 201–10.

FAO, 2010. Production Yearbook for 2011. FAO: Rome, Italy.

Greene W, 2010. A stochastic frontier model with correction for sample selection. Journal of Productivity Analysis 34: 15–24.

Jondrow J, Lovell CAK, Materov IS & Schmidt P, 1982. On the estimation of technical inefficiency in the stochastic frontier production function model. Journal of Econometrics 19: 233–8.

Kambaska KB, Santilata S, Trinanth M & Debashrita P, 2009. Response of vine cuttings to rooting in different months in three *Dioscorea* species. Journal of Nature and Science 7: 48–51.

Kenyon L & Fowler M, 2000. Factors affecting the uptake and adoption of output of crop protection research on yams in Ghana. Unpublished Paper, Natural Resource International Limited, UK.

Kodde DA & Palm FC, 1986. Wald criteria for jointly testing equality and inequality restrictions. Econometrica 54: 1243–6.

Margono H, Sharma SC, Sylwester K & Al-Qalawi U, 2011. Technical efficiency and productivity analysis in Indonesian provincial economies. Applied Economics 43: 663–72.

Ministry of Food and Agriculture, 2010. Agriculture in Ghana: Facts and figures. Accra: Statistics Research and Information Directorate.

Mouelhi RBA, 2009. Impact of the adoption of information and communication technologies on firm efficiency in the Tunisian manufacturing sector. Economic Modelling 26: 961–7.

Murova O & Chidmi B, 2013. Technical efficiency of US dairy farms and federal government programs. Applied Economics 45: 839–47.

Oduol JBA, Binam AJN, Olarinde L, Diagne A & Adekunle A, 2011. Impact of adoption of soil and water conservation technologies on technical efficiency: Insight from smallholder farmers in Sub-Saharan Africa. Journal of Development and Agricultural Economics 3: 655–69.

Solís D, Bravo-Ureta BE & Quiroga R, 2009. Technical efficiency among peasant farmers participating in natural resource management programmes in Central America. Journal of Agricultural Economics 60: 202–19. doi: 10.1111/j.1477-9552.2008.00173.x

Villano RA & Fleming EM, 2006. Technical inefficiency and production risk in rice farming: Evidence from Central Luzon, Philippines. Asian Economic Journal 20: 29–46.

Wiredu AN, Gyasi KO, Saaka SSJ, Asante BO & Mensah-Bonsu A, 2012. Factors affecting proportions of land allocated to the mini-sett technology by yam producers in Northern Ghana. African Journal of Agricultural Research 7(29): 4158–66.