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Impact of Farmer Mentorship Project on Farm Efficiency and Income in Rural Ghana

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Abstract

This paper examines the impact of participation in Agricultural Value Chain Mentorship Project on farm efficiency and income of soybean farmers in Northern Region of Ghana. Due to the exogenous and non-random assignment of the intervention, propensity score matching analysis was used to estimate impact on a cross-section of 200 smallholder farmers. Participation in farmer mentorship project impacts positively on farm technical efficiency by 28 percent. However, participation did not significantly translate into higher farm income. This finding suggests that exposing farmers to agricultural development projects may directly increase their technical capability wtihtin the short term but does not guarantee higher income. The design of any agricultural development project must incorporate the specific needs of farmers to ensure ownership, increased participation and sustainability.

Keywords: impact, farmer mentorship project, efficiency, farm income, rural Ghana, propensity score matching

1. Introduction

Northern Region accounts for 40 percent of agricultural land in Ghana with high potential of being an agricultural hub thus described as the bread basket of Ghana (MoFA, 2010). Agricultural productivity in the region is however low as a result of myriad of biotic and abiotic constraints, including low use of improved seeds, poor soil health, inadequate soil amendments, poor crop management practices, inadequate extension services, weak research-extension linkages, inadequate access to cultivation equipment, limited access to credit among others (MoFA, 2010). In addressing some of the major agricultural challenges in the Northern Region of Ghana, the Agricultural Value Chain Mentorship Project (AVCMP) was approved by Alliance for a Green Revolution in Africa (AGRA).

The AVCMP support grant was awarded through AGRA with funding from the Danish International Development Agency (DANIDA) in order to contribute towards the Government of Ghana's objective of achieving food security and becoming an agro-industrial economy by strengthening the capacity of agro-dealers, small-medium enterprises and FBOs in the Northern Region of Ghana. The support grant was awarded to the International Fertilizer Development Center (IFDC) and its collaborating partners, the Ghana Agricultural Associations Business and Information Centre (GAABIC) and Savanna Agricultural Research Institute (SARI) of the Council for Scientific and Industrial Research (CSIR). The project was implemented in sixteen districts in the Northern Region of Ghana focusing on rice, soybeans and maize value chains. Several improved agricultural technologies and practices were extended to farmers including mentoring sessions on group animation, capacity building on entrepreneurship, linking of farmers to inputs and services, airing of radio programs, videos shows, on-stage drama, and distribution of print materials and establishment of on-farm demonstrations.

Farmer Based Organizations (FBOs) were the main vehicles through which the AVCMP was implemented. Existing FBOs that were formed by previous projects/institutions (such as the Millennium Development Authority, SEND Ghana, Rice Sector Support Project, Northern Rural Growth Program among others) were specifically targeted, primed and trained to participate in the project. Prior to the implementation of the AVCMP, the FBOs appeared not to be well animated with some of them existing as loose groups (it is not uncommon for a farmer to join an FBO for the purpose of benefitting from an intervention and afterwards show disinterest in the group). The FBOs were thus sensitized to restructure in order to list members that the group thought could enable them to achieve their objectives. Hence, even though the FBOs were specifically targeted, FBO membership and consequently participation in the project was left in the hands of the FBO themselves. The assignment of the project in the target areas was therefore exogenous and non-random.

The CSIR-SARI was tasked with the productivity component designed to achieve the three main outcomes. These outcomes are increased smallholder farmers' access to farm inputs (seeds and fertilizers) and integrated soil fertility management (ISFM) technology; improve capacity of national institutions to upscale ISFM; and increased awareness and use of ISFM technologies among smallholder farmers. Capacities of key stakeholders have been built through the implementation of project activities such as trainings, demonstrations, and partnership with the media to improve the facilitation and scaling up of ISFM technology adoption in the target zones. It is expected that the project will enhance smallholder farmers' access to timely inputs and subsequently generate higher output for both household utilization and commercialization.

Development interventions have been shown to cause significant changes in food security (Amaza et al., 2009), and poverty (Awan et al., 2011). However, some interventions have not caused such changes. A study by Kinati, Bekele and Chinnan (2014) in Central Rift Valley of Oromia using the propensity score matching revealed that participation in farming research group intervention increased participant households' productivity on average by 36 percent. Evidence in literature (Falola & Adewumi, 2013) suggests a positive relationship between mobile telephony and the farmers' technical efficiency. However, majority of the farmers were not members of any agricultural association and had no access to extension services through which they could be trained on the inherent benefits of using the technology for farm activities. Davis et al. (2010) investigated the impact of participation in farmer field school (FFS) on agricultural productivity and poverty in East Africa (Tanzania, Kenya and Uganda). They established that participation in FFS increase income by 61 percent for the pooled data despite differences at the country specific levels. Saigenji and Zeller (2009) examined the potential of contract farming as a rural development tool by revealing its effect on productivity and income of smallholders in tea production in north-western Vietnam. The results from the stochastic frontier model show that contract farming in tea production achieved significantly higher technical efficiency compared to non-contract farming. Finally, the impact of contract participation on income using the propensity score matching also revealed a significant positive effect of USD 0.5 daily per capita. In measuring the impact of Ethiopia's new extension program on the productive efficiency of farmers, Alene and Hassan (2003) used the robust stochastic efficiency decomposition technique that accounts for scale effects to derive the technical, allocative and overall productive efficiency for participant and non-participant farmers of the new extension programme. They established that both categories of farmers have considerable overall productive inefficiencies. Based on the results they concluded that no empirical evidence of a positive impact of new extension programmes on overall productive efficiency in both agro-climatic zones.

The design and implementation of the AVCMP was expected to impact on farm performance and welfare outcomes. However, there is currently no evidence-based information on the impact of the project on farm efficiency and income. According to Maredia et al. (2014), as public and more especially private investment in development efforts is increasing, there is the need to provide evidence of impact in order to justify continuous investment or otherwise. The present study provides empirical evidence of the impact of participation in the farmer mentorship project on efficiency and income of smallholder farmers in Northern Region of Ghana. In addition, the study provides empirical contributions to the evolving impact literature and relevant information for informed policy decisions.

2. Method

2.1 Measuring Technical Efficiency

Technical efficiency is the ability of a firm to obtain maximum output from a given set of inputs (Farrell, 1957). It is estimated by either parametric or non-parametric approach. The parametric approach presents a technology frontier in a simple mathematical form and also assumes non-constant returns to scale. The non-parametric approach uses methods such as Data Envelopment Analysis (DEA) while the parametric approach uses econometric methods consisting of either deterministic or stochastic modeling. The deterministic model regards all deviations in output as technical inefficiency effects regardless of the fact that, deviations in output could be beyond the control of the producer (Onumah, Brümmer, & Hörstgen-Schwark, 2010). The Stochastic Frontier Production allows for estimation of the household efficiency score by accounting for factors beyond the control of each producer. Additionally, it helps to understand the factors that determine technical inefficiency of farm households. The stochastic frontier approach was preferred and used for the present study because of the inherent stochasticity involved (Aigner, Lovell, & Schmidt, 1977; Meeusen & Van den Broeck, 1977).

The transcendental logarithm (translog) production function is assumed for this study based on the hypothesis test. The result of the hypothesis test is not reported in this study. The function is specified as:

$$InY_i = \beta_0 + \sum_{j=1}^{5}\beta_j InX_j + 0.5\sum_{j=1}^{5}\sum_{i=1}^{5}\beta_{ji} InX_j InX_i + \left(V_i - U_i\right) \tag{1}$$

Where Y_i is the output of soybean produced in 2012 season by the *ith* farmer and measured in Kg/ha. X_j represent vectors of input namely size of the soybean farmer, hired and family labour, and quantity of seed. β_j is a vector of unknown parameters to be estimated. The V_j is the random error assumed to be independently and identically distributed as $N(0, \sigma^2)$. The U_i is the non-negative $U_i \geq 0$ inefficiency error term. The condition that U_i is non-negative ensures that all observations lie on or below the stochastic production frontier (Aigner et al., 1977; Coelli et al., 2005; Onumah et al., 2010). Following from Battese and Coelli (1995), the technical inefficiency effect is defined as:

$$U_i = \delta_0 + \sum_{i=1}^{13}\delta_i Z_i + W_i \tag{2}$$

Where Z_i is a vector of explanatory variables associated with the technical inefficiency effect which could include socioeconomic and farm management characteristics (district of residence, participation in AVCMP, sex, age, years of farming experience, marital status, years of formal education, nativity status, access to electricity, use of production credit, access to extension service, number of trainings received and household size). δ_i is a vector of unknown parameters to be estimated and W_i are random variables such that $W \geq \delta_i Z_i$. Equations (1) and (2) were estimated using the maximum likelihood single-stage estimation procedure to obtain the technical efficiency scores.

2.2 Measuring Farm Income

Participation in farmer mentorship project is expected to affect resource allocation, productivity and subsequently farm income. The gross farm income was obtained by summing all the revenue from sale of crops, livestock and livestock products as well as home consumption of farm produce valued at local market prices. The farm income was generated by deducting all production costs such as fertilizer, seed, pesticides, hired labour, animal feed, veterinary etc. incurred by households within the 12-month prior to the survey. The farm income was expressed in annual per adult equivalent (AE) (Note 1) basis to estimate the per capita income adjusted for the age structure of the household.

2.3 Measuring Impact

The impact evaluation of the intervention on the outcome variable was constructed within the counterfactual (Note 2) framework. Technically, the counterfactual analysis enables evaluators to attribute cause and effect between interventions and outcomes. The key challenge in impact evaluation is that the counterfactual cannot be directly observed and must be approximated with reference to a comparison group (Winters, Salazar, & Maffioli, 2010). The average outcome that the treated individuals would have obtained in the absence of treatment is not observed. In such types of casual inference, the estimation of treatment effects in the absence of information on the counter-factual poses an empirical problem known as the problem of filling in missing data on the counter-factual (Becker & Ichino, 2002; Dehejia & Wahba, 2002; Rosenbaum & Rubin, 1983). The challenge is to find a suitable comparison group with similar covariates and whose outcomes provide a comparable estimate of outcomes in the absence of treatment.

The treatment effect estimation approach was used by this study to determine the impact of participation in AVCMP on technical efficiency and farm income due to its ability to produce consistent estimates of impacted outcomes (Imbens & Wooldridge, 2009). It is assumed that the smallholder farmers had two hypothetical potential technical efficiency outcomes, Z, given participation status (T) such that $Z = Z_0$ if $T = 0$ and $Z = Z_1$ if $T = 1$. The average treatment effect (ATE) for a randomly selected household is expressed as:

$$ATE = E(Z_1 - Z_0) \tag{3}$$

Given the treatment status, the average treatment effect on the treated (ATT) which measures the impact of participation on those individuals who participated in the AVCMP (i.e. T=1) is given as:

$$ATT = E((Z_1 - Z_0) \mid T = 1) \tag{4}$$

Given the fact that the average of a difference is the difference of the averages, the ATT can be rewritten as:

$$ATT = E\left(Z_1 | T = 1\right) - E(Z_0 \mid T = 1) \tag{5}$$

Self-selection among participants is one of the major challenges with ex-post evaluation studies given that participation may depend on the innate characteristics especially where there is no ex-ante study to assess the behavior of treated group before being treated (Abate et al., 2013). The AVCMP was exogenously assigned to non-randomly sampled farmers. However, the estimation of the participation and outcome equations could be interdependent such that participating in AVCMP can increase output (technical efficiency and farm income) and as such richer and technically efficient households may be better disposed toward participating in AVCMP. Thus, treatment assignment is not random, with the group of farmers being systematically different. Specifically, selection bias occurs if unobservable factors influence both the error terms of the outcome equation, and that of the participation choice equation, thus resulting in correlation of the error terms of the outcome and participation choice specifications (Greene, 2003). In such situation, the estimation of the outcome (efficiency and farm income) with ordinary least squares (OLS) will lead to biased estimates.

Myriads of methods have been used to address the problem of self-selection bias. The Heckman two-step model has been used to address selection bias especially when the correlation between the error terms is greater than zero. The model however, depends on restrictive assumption of normally distributed errors. The instrumental variable approach has also been used with major limitation of difficulty in the identification of an appropriate instrument in the estimation. Additionally, both OLS and IV procedures tend to impose a linear functional form assumption implying that the coefficients on the control variables are similar for adopters and non-adopters (Ali & Abdulai, 2010). Unlike the parametric methods, propensity score matching requires no assumption about the functional form in specifying the relationship between outcomes and predictors of outcome. Due to the shortcomings of the two methods, propensity score matching (PSM) technique is therefore used to control for the selection bias since it accounts for the differences between the outcomes of the treated and comparison groups (Francesconi & Heerink, 2010; Bernard, Taffesse, & Gabre-Madhin, 2008; Godtland et al., 2004). The PSM provides unbiased estimate through controlling for observable confounding factors and in reducing the dimensionality of the matching problem (Becker & Ichino, 2002; Rosenbaum & Rubin, 1983).

2.4 Propensity Score Matching Methods

There are several non-parametric estimation techniques that have been used in impact studies. The propensity score matching method is a non-parametric technique that does not require functional form and distributional assumptions. The PSM also assumes conditional independence and the presence of a reasonable overlap of propensity scores (common support) (Winters et al., 2010). The method is intuitively attractive as it helps in comparing the observed outcomes of treated with the outcomes of the counterfactual control group (Heckman et al., 1998). It helps to evaluate programs that require longitudinal datasets using single cross-sectional dataset where the former does not exist. Despite its advantages, it requires enough data that must be available or feasible to produce experimental treatment effect results. The PSM method basically matches observations of participant and non-participant farmers according to their predicted propensity of participation in AVCMP (Rosebaum & Rubin, 1983; Heckman et al., 1998; Smith & Todd, 2005; Wooldridge, 2005). In the first step, the conditional probability of participation (propensity score) is estimated using the Probit model by controlling for observed household characteristics. In order to establish similarity in distribution of propensity scores between participants and non-participants farmers, a balancing test (Note 3) was conducted. The second step involves the estimation of the average treatment on the treated (ATT) using the matching methods. Different matching algorithm such as the Nearest neighbor, Radius, Local linear and Kernel matching methods were used to compute the average treatment on the treated. The “teffects” (Note 4) commands were also used to compare the ATT values for the various estimation methods.

The analysis was further subjected to test of unobserved heterogeneity. According to Becker and Caliendo (2007), Keele (2010), Rosenbaum (2002), Rosenbaum and Rubin (1983), unobserved heterogeneity (hidden bias) occurs when unobserved variables influence both the treated variable and outcome variable simultaneously. In the absence of experimental data, it is not possible to estimate the magnitude of selection bias (Rosenbaum, 2002). Secondly, the Rosenbaum bounds sensitivity analysis is used to evaluate the presence of unobserved heterogeneity when the key assumption is relaxed by a quantifiable increase in uncertainty.

3. Results

3.1 Descriptive Characteristics of Farm Households by Participation Status

The characteristics of the selected farm households by participation status are presented in Table 1. About 26 percent of the sampled farmers participated in the AVCMP. Based on the results, it is observed that significant differences exist in the means of sex, age, use of production credit, access to extension services, and technical efficiency of participants and non-participant farmers. Participant farmers are relatively younger; receive more production credit, and have higher access to extension services. Farm income, farm income per adult equivalent, farm size and output from soybean did not differ significantly for both participant and non-participant farmers. At this stage, conclusion cannot be made with regard to the causal effect of participation in AVCMP on technical efficiency and farm income.

Table 1. Descriptive characteristics by treatment status and test of mean difference

Variable	Participants (N=51)	Non-participants (N=149)	Prob.
Sex	0.49 (0.50)	0.32 (0.47)	0.032**
Age (year)	37 (9)	41 (13)	0.061*
Years of formal education	1(2.71)	2(4.19)	0.089*
Years of farming experience	5 (3)	5 (2)	0.122
Nativity status	0.94 (0.24)	0.97 (0.16)	0.286
Household size	9 (6)	10 (5)	0.350
Total labour used for farming activities	82.82 (36.86)	97.51 (78.32)	0.199
Use of production credit	0.47 (0.50)	0.21 (0.41)	0.000***
Access to extension services	0.63 (0.49)	0.39 (0.49)	0.003***
Number of trainings received	2.37 (1.07)	2.68 (1.22)	0.114
Area under soybean production	0.70 (0.32)	0.84 (0.55)	0.100
Output of soybean	0.89 (0.68)	1.051 (0.91)	0.244
Technical efficiency	0.64 (0.22)	0.49 (0.29)	0.001***
Proportion of area under soybean	0.27 (0.45)	0.21(.029)	0.270
Farm income	598.50 (463.41)	709.43 (615.37)	0.244
Farm income per adult equivalent	136.31 (89.72)	169.98 (339.90)	0.490

Note. *S*tandard deviations are in parentheses. The *t*-statistics was used for two groups mean comparison. ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.10$; Exchange Rate: 1 USD = GH¢ 2.4.

3.2 Determinants of Farmers Technical Efficiency

The output of soybean is significantly determined by land, and interactive terms such as hired and family labour, hired labour and seed, and land and seed. The coefficient of the production frontier variables indicates that, if land under soybean cultivation increased by 1 percent, then the mean production of soybean is estimated to increase by 0.88 percent (Table 2). The relatively high land elasticity value reflects the high land-use intensity in Northern Region of Ghana. The use of hired, family and other inputs (herbicide) reduce production of soybean by 0.03 percent, 0.03 percent and 0.04 percent respectively despite not significant (Table 2).

Technical inefficiency of farm households is significantly associated with district of residence of the farmer, age, participation in AVCMP, number of years of farming, marital status, use of production credit, and number of trainings received (Table 2). Participation in AVCMP significantly improved soybean farmers' technical efficiency by 1.70 units. Results of the Maximum Likelihood Estimates (MLE) of stochastic production frontier and technical inefficiency model can be found in Table 2. The value of gamma indicates that there is 100 percent variation in output due to technical inefficiency. This indicates that the technical inefficiency effects are a significant component of the total variability of soybean output (Table 2). However, the crux of the present study focused on impact of the binary decision of participation on technical efficiency and farm income.

Table 2. Maximum likelihood estimates of stochastic production frontier and technical inefficiency model

Variable	Coefficient	Std. Error	T-Ratio
Production Frontier			
Constant	-0.079	0.180	-0.436
Ln(Hired Labour)	-0.03	0.05	0.67
Ln(Family Labour)	-0.03	0.09	0.35
Ln(Other inputs)	-0.04	0.03	1.21
Ln(Land)	0.88***	0.08	11.63
Ln(Seed)	0.02	0.06	0.37
0.5(Ln Hired Labour)^2	-0.05	0.05	1.05
0.5(Ln Family Labour)^2	-0.05	0.16	0.33
0.5(Ln Other input)^2	-0.04	0.11	0.35
0.5(Ln Land)^2	0.32*	0.22	1.46
0.5(Ln Seed)^2	-0.09	0.21	0.41
Ln(Hired Labour)* Ln(Family Labour)	-0.09***	0.03	2.65
Ln(Hired Labour)* Ln(Other inputs)	-0.02	0.04	0.45
Ln(Hired Labour)* Ln(Land)	0.05	0.05	0.97
Ln(Hired Labour)* Ln(Seed)	0.14***	0.04	3.47
Ln(Family Labour)* Ln(Other inputs)	-0.04	0.09	0.41
Ln(Family Labour)* Ln(Land)	0.11	0.09	1.27
Ln(Family Labour)* Ln(Seed)	0.09	0.13	0.66
Ln(Other inputs)* Ln(Land)	-0.02	0.08	0.28
Ln(Other inputs)* Ln(Seed)	-0.03	0.06	0.60
Ln(Land)* Ln(Seed)	0.27*	0.15	1.79
Constant	0.71***	0.05	14.13
Technical Inefficiency Model			
District of residence	0.72***	0.27	2.68
Participation in AVCMP	-1.70***	0.34	5.00
Sex	0.25	0.49	0.50
Age	-0.03***	0.01	2.57
Years of farming experience	0.24*	0.13	1.84
Marital status	-1.15*	0.49	2.35
Years of formal education	-0.05	0.04	1.33
Nativity status	-0.73	0.52	1.41
Access to electricity	0.01	0.41	0.01
Use of production credit	1.12*	0.64	1.76
Access to extension service	0.02	0.61	0.03
Number of trainings received	-0.24*	0.10	2.42
Household size	-0.03	0.06	0.50
Constant	2.25*	1.08	2.08
Sigma-squared	1.00**	0.38	2.64
Gamma	1.00***	0.02	58.37
Log likelihood function	140.35		

Note. ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.10$.

3.3 Technical Efficiency Score, Farm Income and Estimated Probability of Participations by Treatment Status

The average technical efficiency scores and farm income per adult equivalent based on participation are summarized in Table 3. It is observed that on the average, participant farmers had significantly higher technical efficiency (0.64) compared to the non-participant farmers (0.53) at the 1 percent level of significance. However, the opposite is true for farm income per adult equivalent. Non-participant farm households on the average recorded a relatively higher income (USD70.83) compared to the participant farm households (USD56.80). The participant households can therefore be described as more technically efficient with relatively lower farm income. The minimum technical efficiency for the non-participant farmers is 0.02 above the participant farmers. However, both categories of farmers recorded the same maximum technical efficiency scores. Participant farm-households recorded higher farm income at the average technical efficiency score of 0.64 (Table 3). Consequently, farm income decreases beyond the average technical efficiency score. It is also possible that other factors apart from the participant households may have contributed significantly to technical efficiency gains and farm income. It is therefore imperative to subject the results to further analysis in order to establish the casual effect.

Table 3. Technical efficiency score by participation status

Categories	Technical Efficiency		Overall (N=200)	Farm Income per adult equivalent (GH₵)		Overall (N=200)
	Participant (N=51)	Non-participant (N=149)		Participant (N=51)	Non-participant (N=149)	
≤0.50	18	56	47	160.37	204.28	200.03
0.51-0.60	29	6	12	166.94	106.43	144.25
0.61-0.70	16	9	11	153.61	127.18	135.99
0.71-0.80	12	7	8	88.38	141.96	121.87
0.81-0.90	14	11	12	125.30	128.20	127.32
0.91-1.00	12	11	11	64.19	122.43	106.55
Mean	0.64	0.49	0.53	136.31	169.98	162.00
Min	0.02	0.04	0.02	9.23	9.78	9.23
Max	0.98	0.98	0.98	368.18	3600	3600
Std. Dev	0.214	0.287	0.04	89.72	339.90	297.60

Note. Exchange Rate: 1 USD = GH₵ 2.4 (2013).

The distribution of the propensity scores for participant and non-participant farmers are presented in Figure 1. Common support (Note 5) region exists between the categories of farmers across the various propensity scores. However, beyond a propensity score of 0.6, nine (9) of the participant farmers fell within the off-support region. The households' off-support regions were not included in the matching processes. The exemption of these households has minimal effects on reliability of the matching results. In fact the common support provides adequate sample for estimating the PSM impact parameter.

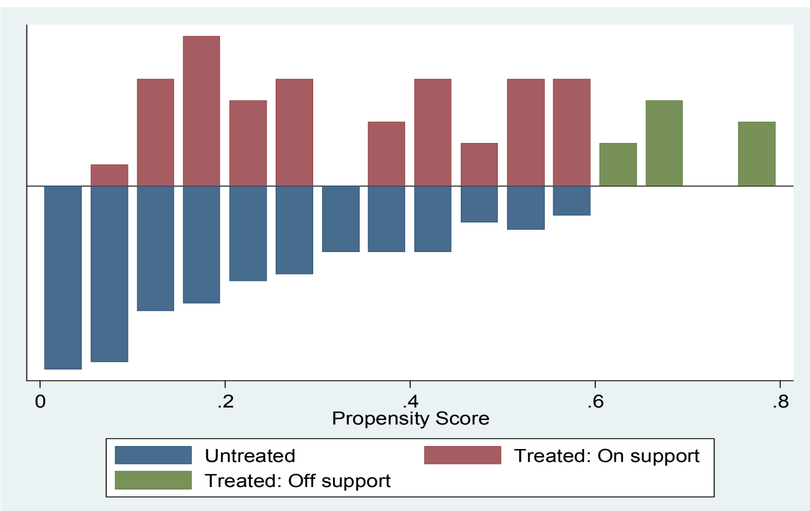

Figure 1. Distribution of common support region by participation status

3.4 Determinants of Participation and Average Impact of Participation on Technical Efficiency

The Probit model was used to estimate the conditional probability of participation (propensity score) given observed household characteristics where the dependent variable equals one if the household had participated and zero otherwise. Appendix 2 in the appendix shows the summary of the Probit result. Participation in agricultural development projects depend on both internal and external factors. For the present study, the farmers were selected to participate in the AVCMP based on socio-demographic, economic and institutional factors. Participation in AVCMP is significantly determined by years of farming experience (5%), number of years of education (10%), use of production credit (5%), access to extension services (5%), number of training received (5%), total labour allocated for soybean production (5%), and access to electricity (10%) (Appendix 2).

Appendix 3 shows the results of the balancing tests. The unmatched sample before the matching fails to satisfy the balancing property as there were significant differences between the means of years of formal education, use of production credit, access to extension services, and access to electricity (Appendix 3). However, the matched sample shows no significant difference in the observed characteristics between participant and non-participant farmers. The balancing property was satisfied per the results.

The average treatment effect on the treated (ATT) using different matching methods is presented in Table 4. The standard errors of the impact estimates are calculated by bootstrap using 50 replications for each estimate. Inverse Probability Weighting (IPW) (Note 4) method was also employed to complement the results. The results revealed that participation in AVCMP had a positive impact on technical efficiency. However, participation also impacted positively on farm income although was not significant. For all the matching methods, positive impact was realized at the 5 percent level of significance suggesting consistency in the results. Per the results, farmers who participated in the AVCMP respectively recorded 28 percent and USD18 increase in their technical efficiency and farm income (Table 4).

Table 4. Impact of participation in AVCMP on technical efficiency

Technical Efficiency Impact		
Matching algorithm[a]	Coefficient (ATT)	Bootstrap Std. Error
Kernel	0.279	0.073***
Radius	0.279	0.075***
Nearest Neighbour	0.279	0.075***
Local Linear	0.279	0.074***
Method	Coefficient (ATT)	AI Robust Std. Error
Inverse Probability Weighting	0.210	0.039***
Farm Income Impact		
Method	Average Treatment Effect on Treated (ATT)	AI Robust Std. Error
Inverse Probability Weighting	44.16	0.295

Note. ***: $p < 0.01$; **: $p < 0.05$; and *: $p < 0.10$; Exchange Rate: 1 USD = GH¢ 2.4 (2013).

[a]ATT estimates of kernel, radius, nearest neighbor and local linear matching were obtained by implementing ‘psmatch2’ command in Stata.

Conditional independence is assumed per this study implying that participation is based on observable characteristics such that variables simultaneously influencing participation and technical efficiency are observable. The result of sensitivity analysis (positive and negative) for all the matching methods is shown in Appendix 4. The result focused on the Kernel matching with the positive significance (sig+). It is observed that the results are insensitive to any hidden bias that may undermine the estimated impact of the programme.

4. Discussion

4.1 Determinants of Production and Technical Efficiency

The study observed that participant households are more technically efficient than non-participant households. Given the technology currently used, participant farmers and non-participant farmers were respectively producing maize at about 64 percent and 49 percent of the potential frontier output. The implication is that in the short run, there is capacity for increasing technical efficiency in soybean production by 36 percent and 51 percent respectively without necessarily varying the existing input levels. Production of soybean in Saboba and Chereponi districts is largely determined by land. The relatively high land elasticity value reflects the high land-use intensity in Northern Region of Ghana. The high land-use intensity is not complemented with the use of improved technologies thus impacting relatively lower on farm output. Investment in land productivity through the use of integrated soil fertility management practices must be encouraged and intensified in Northern Region of Ghana where soil fertility is a major challenge. Some studies have also established a positive significant effect of land on output (Asante et al., 2014; Abate et al., 2013; Chirwa, 2007; Idiong, 2007). Al-hassan (2008) also reported a positive relationship between farm size and rice production in northern Ghana. The non-significant and negative effect of farm inputs such as hired, family and other inputs (such as herbicides, insecticides etc.) on soybean production can largely be attributed to the inconsistency and inadequate skills in the use of farm labour and other farm inputs. Sensitization and promotion of the use of certified seed was a major activity of the AVCMP. The project also facilitated access to seed to resource-poor farmers. Seed influenced soybean output positively despite not significant. The plausible reason could be that farmers buy certified seeds but not in the right quantity thus affecting plant population and output. Secondly, it is also possible that farmers lack the financial resource to invest in high yielding technologies that complement use of certified seeds. Based on the results, it is important to continuously sensitize and facilitate access to improved seed and timely credit to farmers if increase in production volume of soybean is to be achieved. Kebede and Adenew (2011) established a positive and significant effect of seed on output of wheat in Ethiopia. The return to scale value of 0.88 indicates that on the average, soybean farmers in Saboba and Chereponi districts are operating under decreasing returns to scale. The result implies that a percentage increase in all factors of production will result in 0.88 percent decrease in output *ceteris paribus*.

4.2 Determinants of Participation in AVCMP

Participation in AVCMP depends on factors such as years of farming experience, number of years of education, use of production credit, access to extension services, number of training received, total labour allocated for soybean production, and access to electricity (Appendix 2). Farmers' experience plays a critical role in participation in development programmes. Experienced farmers may depend on their skills and innovations acquired over the years through experimentation thus limiting their participation in any developmental programmes. Also, social networks available to experience farmers enhance their productive and commercial decisions thus less likely to participate.

The probability of participation in AVCMP reduces with increase in the number of years of formal education. Educated farmers may be engaged in agriculture as a secondary occupation and may also serve as nodal points for most extension programmes which impacts negatively on their willingness to participate in any agricultural development projects. Alternatively, educated farmers may allocate their resource and skills to other off-farm employment opportunities which is more remunerating (Martey et al., 2012; De Janvry & Saddoulet, 2001). The results confirms the findings of Khan et al. (2012) and Farid et al. (2009) who both reported a negative relationship between education and rural women's participation in agricultural activities. The result however, contradicts the findings of Tambo and Abdoulaye (2011), Enete and Igbokwe (2009), and Nzomoi et al. (2007). According to Nnadi and Akwiwu (2008), education increases the likelihood of youth participation in rural agriculture in Nigeria.

Access to production credit enables farmers to purchase inputs on time and also invest in farm technologies that have the potential of increasing output. Agricultural development projects usually facilitate linkage of farmers to production credit. It is a common practice for most donors to link financial support to agricultural projects in most developing countries. Some agricultural projects guarantee farmers access to credit whilst others may have guaranteed funds. Such arrangements are likely to increase participation of farmers in agricultural development projects. Most studies have found a positive effect of credit on participation (Martey et al., 2013; Asante, Afari-Sefa, & Sarpong, 2011; Nzomoi et al., 2007; Mussei et al., 2001).

Farmers with access to extension services are more likely to increase their participation in agricultural development projects. Agricultural related programmes and projects have been mostly implemented through the Directorate of Agricultural Extension Services of the Ministry of Food and Agriculture who are tasked to identify, prime and extend support to farmers and farmer-based organizations. Farmers who have contact with agricultural extension agents are therefore more likely to benefit from agricultural interventions (Etwire, Martey, & Dogbe, 2013). There is a high possibility of selecting farmers into any agricultural development interventions that have established some relationship with extension agents. However, farmers who have had several trainings over the years may be less willing to participate in projects or programmes due to participation fatigue or inability of the project to meet their specific needs. The design of agricultural development project in an integrated approach where the opinions of farmers are solicited will go a long way to influence ownership and participation.

The total man-days allocated to soybean production decreases farmers' participation in AVCMP. Farm demand in terms of labour makes it difficult for farmers to allocate part of their time to other social activities. This phenomenon supports the need to resource farm household with labor saving technologies for effective execution of field activities. Finally, farmers with access to electricity are more likely to obtain agricultural and market information through television, radio and cell phone which may have an effect on their willingness to participate in agricultural interventions. However, the result cannot be generalized for all farmers with access to electricity.

4.3 Impact of Participation in AVCMP on Technical Efficiency and Farm Income

Result of the study has shown that participation in the AVCMP had positive impact on technical efficiency and farm income of farm households in Northern Region of Ghana though the latter is not significant. This suggests that participation in development project does not necessarily improve farm income. It is possible that risk adverse farmers do not immediately implement the knowledge received from mentorship due to their past experience and other external limiting factors. However, impact of the participation on farm income may be realized in the long term. The estimated technical efficiency gain by AVCMP participants is 28 percentage points higher relative to matched non-participants. The results corroborate the findings of Abate et al. (2013) and Elias et al. (2013) who established that participation in agricultural cooperatives increases technical efficiency and productivity of smallholder farmers in Ethiopia respectively. Farmers' technical efficiency can be enhanced through participation in AVCMP. The mentorship project specifically mentored small and medium enterprises, agro-dealers, farmer-based organizations (FBOs), and their member farmers in developing their entrepreneurial and technical skills. The mentorship opportunities available to participant farm-households increase their capacity and access to farm inputs on time. Specifically, the positive impact may be attributed to the business training, farm demonstrations on integrated soil fertility management practices as well as linkage to both factor and output markets. These benefits were intended to improve their orientation towards farming and allocation of farm inputs to achieve the maximum output. High level of technical efficiency is essential for competitiveness and profitability in farming. This suggests the need for sustaining the project as well as encouraging farmers to willingly participate without monetary enticement. Furthermore, the result justifies investment in human capital to enhance farmers' knowledge, awareness of existing technologies and practices, and technical competence in farming.

5. Conclusion

This study provided empirical evidence of impact of participation in AVCMP on technical efficiency and farm income of soybean farmers in Northern Region of Ghana. It showed that participation in the project increases technical efficiency significantly. Participation in farmer mentorship programmes improve efficiency by providing easy access to productive inputs and embedded support services such as training, information, and extension on input application. The impact of participation on farm income may be realized in the long run with continuous use of the knowledge acquired from the mentorship project. The main recommendation is that, there should be conscious efforts to enhance participation in such projects/programmes by designing the projects/programmes in such a way that it addresses specific needs of farmers. Finally, policies that promote farmer mentorship projects as a complement to extension services must be austerely promoted.

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Notes

Note 1. We use the OECD adult equivalent scale which is given by: 1+0.7(A-1)+0.5C, where A and C represent the number of adults and children in a household, respectively.

Note 2. The 'counterfactual' measures what would have happened to beneficiaries in the absence of the intervention, and impact is estimated by comparing counterfactual outcomes to those observed under the intervention.

Note 3. Balancing test compares a simple means of household characteristics within the treatment group to the corresponding comparison groups created by the matching techniques before and after matching as a complement.

Note 4. Stata treatment effects reference manual: potential outcomes/counterfactual outcomes (StataCorp 2013).

Note 5. Common support refers to the values of the propensity scores where both participant farmers and non-participant farmers are located.

Appendix

Appendix 1. List of explanatory variables and their a priori expectation

Variable	Description/Measurement	A priori
District of residence	Dummy variable: 1 if farmer resides in Chereponi district and 0 otherwise	+/-
Years of farming experience	Number of years spent in farming measured in years	+
Number of years of education	Years of formal education measured in years	+
Use of production credit	Dummy variable: 1 if farmer has access to credit and 0 otherwise	+
Access to extension services	Dummy variable: 1 if farmer has access to extension and 0 otherwise	+
Number of trainings received in 2012	The number of times a farmer has been trained (number)	+/-
Total labour used for production	The total man-days used per farmer for production	+
Nativity status	Dummy variable: 1 if farmer is a native and 0 settler	+/-
Access to electricity	Dummy variable: 1 if farmer has access to electricity and 0 otherwise	+
Household size	Total number of household size	+

Appendix 2. Determinants of AVCMP participation

Variable	Coefficient	Std. Error	P>|z|
District of residence	0.274	0.234	0.241
Years of farming experience	-0.116	0.049	0.017
Number of years of education	-0.060	0.034	0.074
Use of production credit	0.643	0.273	0.019
Access to extension services	0.701	0.286	0.014
Number of trainings received in 2012	-0.217	0.106	0.040
Total labour used for production	-0.005	0.002	0.022
Nativity status	-0.471	0.530	0.375
Access to electricity	-0.562	0.310	0.070
Household size	0.013	0.023	0.585
Number of observation		200	
LR chi2 (10)		38.49	
Prob > chi2		0.000	
Pseudo R2		0.170	
Log likelihood		-94.306	

Appendix 3. Balancing test of matched sample

Variables	Unmatched Sample			Kernel Matching		
	Mean		P > |t|	Mean		P > |t|
	Treated	Control		Treated	Control	
District of residence	0.51	0.53	0.802	0.50	0.46	0.73
Experience of household head	5	5	0.122	5.14	5.06	0.87
Years of formal education	1	2	0.089	1.19	1.21	0.97
Use of production credit	0.47	0.21	0.000	0.38	0.38	0.99
Access to extension services	0.63	0.39	0.003	0.60	0.57	0.82
Number of past trainings received	2.37	2.68	0.114	2.45	2.43	0.92
Total labour used for production	82.82	97.51	0.199	83.50	81.95	0.88
Nativity status	0.94	0.97	0.286	0.95	0.98	0.55
Access to electricity	0.12	0.25	0.050	0.14	0.12	0.80
Household size	9	10	0.350	9.38	8.98	0.74

Appendix 4. Rosenbaum bounds sensitivity analysis for hidden bias

Critical Value of Hidden Bias (Γ)	Kernel Matching		Radius Matching		Nearest Neighbour		Local Linear	
	Sig+	Sig-	Sig+	Sig-	Sig+	Sig-	Sig+	Sig-
1.00	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082
1.05	0.050	0.127	0.050	0.127	0.050	0.127	0.050	0.127
1.10	0.030	0.185	0.030	0.185	0.030	0.185	0.030	0.185
1.15	0.017	0.252	0.017	0.252	0.017	0.252	0.017	0.252
1.20	0.010	0.326	0.010	0.326	0.010	0.326	0.010	0.326
1.25	0.005	0.405	0.005	0.405	0.005	0.405	0.005	0.405
1.30	0.003	0.485	0.003	0.485	0.003	0.485	0.003	0.485
1.35	0.001	0.562	0.001	0.562	0.001	0.562	0.001	0.562
1.40	0.001	0.634	0.001	0.634	0.008	0.634	0.001	0.634
1.45	0.000	0.700	0.000	0.700	0.000	0.699	0.000	0.700
1.50	0.000	0.757	0.000	0.757	0.000	0.757	0.000	0.757
1.55	0.000	0.807	0.000	0.807	0.000	0.807	0.000	0.807
1.60	0.000	0.849	0.000	0.849	0.000	0.849	0.000	0.849
1.65	0.000	0.883	0.000	0.883	0.000	0.883	0.000	0.883
1.70	0.000	0.911	0.000	0.911	0.000	0.911	0.000	0.911
1.75	0.000	0.933	0.000	0.933	0.000	0.933	0.000	0.933
1.80	0.000	0.950	0.000	0.950	0.000	0.950	0.000	0.950
1.85	0.000	0.963	0.000	0.963	0.000	0.963	0.000	0.963
1.90	0.000	0.973	0.000	0.973	0.000	0.973	0.000	0.973
1.95	0.000	0.980	0.000	0.980	0.000	0.980	0.000	0.980
2.00	0.000	0.986	0.000	0.986	0.000	0.986	0.000	0.986

Note. Γ measures the degree of departure from random assignment of treatment or a study free of bias. The sensitivity analysis is for both-sided significance levels.