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FACTORS INFLUENCING PEST MANAGEMENT DECISIONS AMONG MAIZE FARMING HOUSEHOLDS

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ABSTRACT

Research background: Poor pest management decisions in crop production highly pronounced in most developing countries including Nigeria, result in huge crop losses, human health challenges and environmental degradation, detrimental to sustainable agriculture, food sufficiency and security. Identifying the factors influencing pest management decisions among maize farming households and providing effective solutions by relevant stakeholders can reduce crop losses and reduce the harmful effect to human health and the environment due to harmful pest management practices.
Purpose of the article: The research was carried out to determine the factors influencing pest management decisions among maize farming households in the Federal Capital Territory, Nigeria, in order to provide effective and appropriate solutions capable of enhancing pest management decisions and invariably reducing crop losses due to pests, as well as reduce the harmful effect to human health and the environment caused by harmful pest management and control practices.
Methods: Multistage sampling technique was the sampling method used, where 324 maize farmers were correctly sampled as respondents for this study. Primary data were collected from the respondents using a well-structured questionnaire. The data were analysed using descriptive statistics and multinomial probit model. The multinomial probit model was used to identify factors that influence pest management decisions.
Findings, value added & novelty: The study revealed the use of chemical pesticides as the most used pest management practice among maize farming households in the Federal Capital Territory, Nigeria, while the use of integrated pest management practices was about the least used. Also, result from multinomial probit analysis of the study showed that gender, access to extension services, age and level of education were significant factors that influenced pest management decisions. The study, therefore, recommends the need for relevant non-governmental organisations and government ministries/agencies to engage in the provision of educational facilities and incentives to crop farmers, more robust agricultural extension programmes, input subsidies and farmer field schools, targeted at enhancing pest management decisions in crop production, which can be vital to sustainable and maximized agricultural production, human health and the environment.

Keywords: pest management decisions; multinomial probit; maize farming households; integrated pest management
JEL Codes: R52; R58; H41

INTRODUCTION

Pest management is critical in agricultural production since damage from pests often results in huge economic losses. Crop pests and pathogens are widely seen as significant obstacles to reliable and regular food systems (**Savary *et al.*, 2017**). Some estimates have shown that field and storage pests destroy about 43% of potential crop production in developing African and Asian countries (**Ogendo *et al.*, 2004**). Pest infestations, from insects, weeds, fungi and other highly harmful organisms to crops, have been a major threat to agricultural production worldwide (**Ruttan, 2005**). According to **Savary *et al.* (2019)**, crop pests and pathogens reduce the yield of agricultural production, causing huge economic losses and reduced food security, even so, their global burden and their variation over time and among different agro-ecosystems remains poorly quantified.

Pests are reputed to be one of the major factors limiting maize yield in the savannah agro-ecological zone of Nigeria (**Ismaila *et al.*, 2010**). Maize (*Zea mays*) is a type of cereal, regarded as one of the most important staple foods in the world today. Maize, rice and wheat, together supply more than 50% of global calorie intake (**Knoema's World Data Atlas, n.d.**). The central role of maize as a staple food in Sub-Saharan Africa is comparable to that of rice or wheat in Asia with maize accounting for one-fifth of the calories and protein consumed in West Africa (**Macauley, 2015**).

Pesticides are most commonly and frequently used in managing pests in most agricultural sectors (**Hashemi & Damalas, 2011**). **Sarkar *et al.* (2021)** revealed that pesticide use is seen as the best means to protect crops against pests by most farmers in developing countries. Farmers in developing countries face great risks of exposure from the use of toxic and hazardous pesticides that are restricted or banned in other countries (**Asogwa & Dongo, 2009; Ibitayo, 2006**). Despite the several strategies available for controlling pest, farmers in Nigeria depend highly on the use of pesticides, to the extent where pesticides are treated as substitutes for labour and ploughing services (**Rahman & Chima, 2018**).

According to **FAO (2017)**, adequate decision-making for any intervention on pest management is vital and decisions should be justified both economically and ecologically. Pest management decisions of maize farming households in the Federal Capital Territory (FCT), Nigeria, have not been widely explored in research, and there is also a paucity of information on the factors that influence pest management decisions in the FCT, despite its importance to enhanced crop production, human health and the environment. With sound pest management decisions, losses to crops, especially the maize crop would be reduced and preservation of the environment and human health would be enhanced. Against this backdrop, this study aimed at examining the factors influencing pest management decisions among maize farming households in the Federal Capital Territory, Nigeria. Specifically, the study would identify the pest management practices in use among maize farming households in FCT, and secondly, it would identify factors that influence pest management decisions among maize farming households in FCT.

The following null hypotheses guided the study to achieve the specific objective of identifying factors that influence pest management decisions among maize farming households in FCT: (i) H_{01}: there is no significant relationship between pest management decisions and the socio-economic characteristics of the respondents in FCT; (ii) H_{02}: there is no significant relationship between farm-specific and institutional factors and pest management decisions of the respondents in FCT.

LITERATURE REVIEW

Decision, according to **Nicholson *et al*. (2020)**, is referred to as a conclusion or resolution reached after consideration. Decisions directly connected to actions influence the quality, type and quantity of agricultural output and can have major economic and environmental consequences (**Martin-Clouaire, 2017**). Decision-making is seen as a mental process resulting in the selection of an action among several alternative solutions **(Singe & Gupta, 2017).** The primary drivers of decisions are the farmer's motives, perceptions, beliefs and preferences; thus, farmers' decisions are heterogeneous from farm to farm and also from field to field (**Martin-Clouaire, 2017**).

Pest management is the decision-making process to control the populations of pests in a planned and systematic way by keeping their damage or numbers at economically acceptable levels (**Northeast Region Certified Crop Adviser, 2016**). In the opinion of **Alston (2011)**, pest managers cannot afford to take a pest management action without knowing if it is economically sound, since treating a pest needlessly does not amount to making a profit. According to **Gibb (2015)**, pest management requires knowing the pest population levels and the possible applications of various control tactics in a pest management framework where pest tolerance levels are established and used as decision-making guides to clarify if action against a certain pest is desirable.

Pest management is a crucial part of agricultural production and includes several practices aimed at controlling potentially harmful organisms (insects, weeds, diseases and other pathogens) that may cause severe damage to crop plants, lower product quality and reduce yield (**Hashemi & Damalas, 2011**). According to **Edward-Jones (2007)**, pest management aims at preventing pest damage in the form of decrease in the quality or the quantity of crops. Pest management is a means to reduce pest numbers to an acceptable threshold (**WICC, 2019**). An acceptable threshold refers to an economically justifiable threshold where the application of measures to control pests reduces pest numbers to a level below which additional applications would not be profitable (that is, where additional costs of control exceed additional benefits) (**WICC, 2019**). Complete removal or eradication of pests is not usually an economic or viable option.

According to **Waterfield & Zilberman (2012)**, farmers' pest management decisions relate to balancing the benefits of pest control against their private costs which are also impacted by information constraints, risk attitudes and their various attitudes and preferences to treatment options. **Hashemi & Dalamas (2011)** summarize the complexity of pest management decisions, stating that pest management problems are often complex, requiring detailed information about many factors, where the complexity is made worse in that farmers usually have incomplete information about both the problem and the potential techniques to manage them.

In agricultural systems, the farmer takes the main decisions. According to **Martin-Clouaire (2017)**, decisions that are directly connected to actions also called "operational decisions," influence the output of a farm and therefore have environmental and economic consequences. Developments in technology, growing commercial competition as well as stricter requirements in terms of sociological and environmental aspects make consideration of decision-making ever more important **(Martin-Clouaire, 2017)**.

Many factors affect pest management decisions and which among others include income, level of education, effectiveness of control substances, information, age, farm size, pest incidence and government regulations. A study conducted by **Melkamu (2018)** on maize farmers in East Showa, Ethiopia, showed that sex, education, age, farm experience, labour in man equivalent, awareness on the introduction of chemical pesticides, credit access, income and extension contact were significant determinants in the use of local pest management practices. Similar but fewer factors were seen in a study conducted by **Alalade *et al*.**

(2017) which examined the usage of chemical and biological pests control methods among farmers in Kwara State, Nigeria, where it was reported that age, educational level, household size, farm size and the perceived effect of both chemical and biological pest control methods were significant factors in the usage of chemical and biological pest control methods. Similarly, the results of a study carried out by **Alabi *et al.* (2014)** in Gwagwalada and Kuje Area Councils of the Federal Capital Territory, Nigeria, revealed that farmers' decision to use agrochemical inputs increased with farm size, age, family size, extension services, education-level, experiences in farming but decreased where there were off-farm incomes and access to credits.

In a study conducted by **Samiee *et al*. (2009)**, the level of knowledge showed the highest variation in the adoption level of sustainable integrated pest management (IPM) practices by wheat growers in Varamin County, Iran. Similarly, a survey conducted by **Blake *et al*. (2007)** on the United States Massachusetts cranberry grower community on the adoption of available IPM practices, showed that highly experienced, full-time growers in charge of large operations frequently used more IPM practices than part-time, less experienced growers who managed smaller farms.

Factors affecting pest management decisions can be identified using multinomial regression models. Multinomial regression models are applied in analysing data where the categorical response variable has more than two possible outcomes while the independent variables may be categorical, continuous, or both (**Hosmer & Lemeshow, 2013**). Multinomial probit (MNP) and multinomial logit (MNL) models are multinomial regression models (**Greene, 2012**). The multinomial probit model is a generalization of the probit model used when there are various possible categories that the dependent variable can fall into and has a significant advantage over the multinomial logit model since MNP relaxes the independence of irrelevant alternatives (IIA) restrictions built into the multinomial logit model (**Greene, 2012**). MNP model was used in this study to identify factors that influence pest management decisions among maize farming households in FCT. The response variable included various possible pest management decisions which include physical control, biological control, chemical control, cultural control and IPM.

Multinomial probit and multivariate probit approaches were used in a study carried out by **Velandia *et al*. (2009)** to determine the factors that affect farmers' adoption of crop insurance, spreading sales and forward contracting, while also considering the potential for simultaneous adoption and/or correlation among the adoption decisions. It was reported that the multinomial probit estimation procedure gave the same variables that the multivariate probit analysis revealed as the variables which substantially influenced the risk management tools that producers adopted, which included age, proportion of owned acres, farm size and off-farm income levels. However, the multinomial probit also provided additional information that the multivariate probit did not provide since the former looked at factors affecting the combination of tools utilized by the farmers in the study.

DATA AND METHODS

Study Area

The Federal Capital Territory (FCT) of Nigeria is the study area for this research. FCT is centrally located in Nigeria and has a land area of approximately 8,000 square Kilometres **(Ogidiolu *et al.*, 2012)**. The territory is made up of six area councils, namely: Abuja Municipal, Abaji, Bwari, Gwagwalada, Kuje and Kwali (**Tanko & Muhsinat, 2014**). FCT is of the savanna vegetation with soils which are more of Alluvial and Luvisols, rich for agriculture **(Ogidiolu *et al.*, 2012)**. The vegetation in most parts of FCT is dominated by herbaceous plants which are at times interspersed with shrubs. The soil characteristics are mostly derived from sedimentary rocks and have a strong influence on the morphological characteristics of the local soils. The major crops grown in FCT include maize (*Zea mays*), sorghum (*Sorghum vulgare*), cassava (*Manihot utilsima*), groundnuts (*Arachis hypogaea*), and some other sundry crops such as okra, garden egg and pepper (**Tanko & Muhsinat, 2014**).

Sampling Technique and Sample Size

This study adopted a multistage sampling technique for sample size selection. The study was carried out in three selected area councils of FCT, namely, Kuje, Gwagwalada and Kwali. These area councils were purposively selected because of the preponderance of maize farmers in the areas. The second stage of the sampling involved a simple random selection of three blocks from each of the three selected area councils, making nine blocks. Three villages were then randomly selected from each of the selected blocks in the third stage of sampling, making 27 villages. Agricultural Services departments in the selected area councils provided the list of maize farmers (representing maize farming household heads) which served as the sampling frame for the study. Accordingly, Cochran's formula (Eq. 1) derived for calculating sample size when a population is infinite (**Cochran, 1977; Israel, 2012)** was adopted in calculating the sample size used to select the maize farmers for this study.

$$n_0 = (z^2pq)/e^2 \tag{1}$$

Where:

n_0 required sample size; z selected critical value of desired confidence level (assuming 95% confidence, z = 1.96); p the estimated proportion of an attribute that is present in the population (assuming maximum variability which is equal to 50%, $p = 0.5$); $q = 1 - \mathrm{p} = 0.5$; e desired level of precision (assuming $\pm$ 5% precision, $e = 0.05$).

This resulted in a required sample size of 385. However, 324 respondents (maize farmers) were correctly sampled from 27 selected villages and their responses were used for the analyses.

Method of Data Collection

The primary data used for this study were collected using a well-structured questionnaire. The questionnaire was pre-tested and adjusted to enhance its validity and reliability before administering. The questionnaires were administered to selected farmers in the selected areas through personal interviews, done with the cooperation of some local leaders and staff of Agricultural Services departments in the selected Area Councils. The staff of these Agricultural Services departments who served as data collectors were trained on how to administer the questionnaires.

Econometric Model Specification: Multinomial Probit Model

Multinomial Probit (MNP) model was used to identify factors that influence pest management decisions among maize farming households in the FCT. The dependent variable was pest management decisions which include decisions to use physical control, biological control, chemical control, cultural control and IPM. Applying the structural equation of MNP model by **Greene (2012)** as shown in Eq. (2).

$$U_{ij} = X'_{ij}\beta + \varepsilon_{ij}, \qquad j = 1, \ldots, J, \quad [\varepsilon_{i1}, \varepsilon_{i2}, \ldots, \varepsilon_{iJ}] \sim N[0, \Sigma] \qquad (2)$$

where:

U pest management decision; β parameter of the factors that influence pest management decisions;

X_i factors that influence pest management decisions (socio-economic, farm-specific and institutional factors) and include: X_1 Age of household head (Years); X_2 Household size (number of persons in the household); X_3 Level of Education of household head (1, 'Formal Education'; 0, Otherwise); X_4 Gender of household head (1, Male; 0, Otherwise); X_5 Farm Size (Hectares); X_6 Farming Experience (Years); X_7 Access to Agricultural Extension Services (1, Yes; 0, Otherwise); X_8 Access to credit facilities (1, Yes; 0, Otherwise); X_9 Membership of Cooperative (1, Member; 0, Otherwise); X_{10} Access to Insurance (1, Yes; 0, Otherwise);

ε_j error terms; $j = 1,2, \ldots, J$ for a total of J pest management decision alternatives; $i = 1,2, \ldots, I$ for the total number of farmers.

For the ith farmer faced with J choices, we assume that U_{ij} is the maximum pest management decision among the J alternatives. The term in the log-likelihood that corresponds to the choice of alternative q (Eq. 3).

$$\text{Prob}[\text{choice}_{iq}] = \text{Prob}[U_{iq} > U_{ij}, \quad j = 1, \ldots, J, j \neq q] \qquad (3)$$

The probability for this occurrence (Eq. 4).

$$\text{Prob}[\text{choice}_{iq}] = \text{Prob}[\varepsilon_{i1} - \varepsilon_{iq} < (x_{iq} - x_{i1})'\beta, \ldots, \varepsilon_{iJ} - \varepsilon_{iq} < (x_{iq} - x_{iJ})'\beta] \qquad (4)$$

Hypotheses Testing

The null hypotheses in this study were tested using z-test in the multinomial probit model. The null hypotheses may be accepted or rejected at 95% confidence interval or at various levels of significance (1%, 5% or 10%).

RESULTS AND DISCUSSION

Socio-economic Characteristics of the Maize Farming Households in the Study Area

Table 1 shows the result of socio-economic characteristics of the maize farming households in the study area. The result gives the mean gender of the maize farming household heads as 0.759, which means that 75.9% (about three-quarters) were males. The mean age of the maize farming household heads in the study is 43 years, which implies that most of the farmers were predominantly in their economically active age. This coincides with the mean age of 43 years for sampled smallholder farmers obtained in a study carried out in Gwagwalada and Kuje Area Councils of FCT by **Alabi *et al*. (2014)**.

Education promotes adoption of new technologies and decision-making processes in agriculture. The mean level of education in this study is 0.613, which means that 61.3% (majority) of the maize farmers in this study had formal education and thus, may be able to read and write in English and/or in their local dialect. **Kim *et al.* (2018)** concluded in a study carried out in Malawi, that education is a tool for enhancing an individual's decision-making quality.

The mean number of years in farming of maize farmers in the study is 16 years, which shows high experience in farming. This implies that with such high experience in farming, farmers may be able to make sound decisions in pest management and other farm management activities. The mean access to agricultural extension services by the maize farmers in the study is 0.739 (73.9%). This is similar to a study carried out by **Ototoju & Enete (2016)** where about 71% of food crop farmers in South-West Nigeria had Extension contacts. Agricultural extension service is one of the major sources of enhancing adoption and promotion of agricultural innovations and technology and also enhances farmers' decision-making processes. According to **Alabi *et al.* (2014),** farmers in FCT trust government extension services when it comes to delivery of agricultural information.

Pest Management Practices among Maize Farming Households in FCT

The result in Table 2 is a multiple response set that represents the types and frequency distributions of pest management practices among maize farming households in the study. From the result, the most used pest management practice was the 'use of chemical pesticides' (having 20.6% of the frequency of responses) which was followed by 'planting of cover crops' (13.4%) and 'planting of resistant maize variety' (12.6%). The 'use of IPM practices' (1.1%) was among the least pest management practice used among the maize farming households. There was no reported biological pest management practice.

Table 1: Socio-economic characteristics of the maize farming households in the study area

Variable	Measurement	Mean
Gender	Dummy (1, Male; 0, otherwise)	0.759
Age	Years	43.000
Household size	Units	8.000
Number of years in farming	Years	16.000
Size of maize farm	Hectares	2.400
Level of education	Dummy (1, "Formal Education"; 0, otherwise)	0.613
Access to agricultural extension services	Dummy (1, Yes; 0, otherwise)	0.739
Access to farm credit facilities	Dummy (1, Yes; 0, otherwise)	0.109
Membership of farmer cooperatives	Dummy (1, Yes; 0, otherwise)	0.512
Access to farm insurance	Dummy (1, Yes; 0, otherwise)	0.00

Table 2: Pest Management Practices among Maize Farming Households in the Study Area

Pest Management Practices [a]	Responses		Percentage of
	N Frequency	Percentage (%)	Cases (%)
Use of animal traps	94	7.2	29.0
Hand-picking of insects	18	1.4	5.6
Mulching	35	2.7	10.8
Removal of pest-infested maize plant	74	5.7	22.8
Burning of farmland before planting	45	3.5	13.9
Use of crop rotation	117	9.0	36.1
Adjustment of planting date of maize	55	4.2	17.0
Intercropping maize with other plants	138	10.6	42.6
Planting of cover crops	174	13.4	53.7
Planting of resistant maize variety	164	12.6	50.6
Increased spacing of maize crop	25	1.9	7.7
Timely crop harvesting	15	1.2	4.6
Use of chemical pesticides	267	20.6	82.4
Use of inorganic fertilizer	10	0.8	3.1
Use of maize seeds pelleted with insecticides	54	4.2	16.7
Use of IPM practices	14	1.1	4.3
Total	1299	100.0	400.9

Note: 'a' represents dichotomy group tabulated at value 1(Yes) on a multiple response set; Sample size (n) = 324.
Source: Computed from field data, 2020.

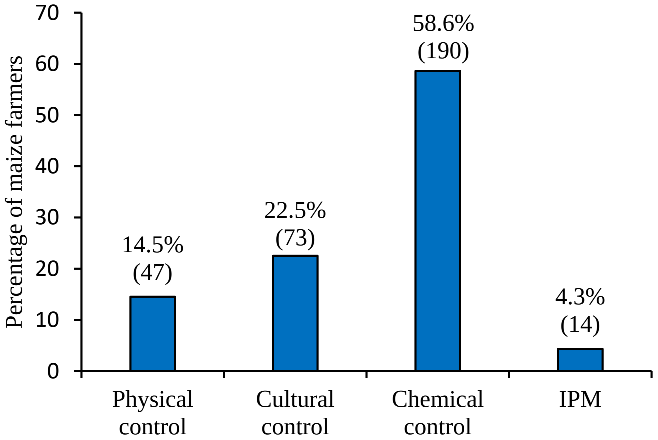

Figure 1: Pest Management Decision Categories Among Maize Farmers in the Study Area
Source: Computed from field data, 2020.

The percentage of cases in the result depicts the percentage of the ratio of the frequency of responses to the sample size of the study, and this for the pest management practice of 'use of chemical pesticides' was 82.4% (represented the highest percentage of cases) and that for the pest management practice of 'use of IPM practices' was 4.3% (represented about the least percentage of cases). The study result of the use of chemical pesticides (82.4%) which depicted the highest percentage of cases, supports the findings of **Hashemi & Damalas (2011)** which states that the application of chemical pesticides is the most frequent means of managing pest in most agricultural sectors. It also supports the study of **Sarkar *et al.* (2021)** which revealed that *pesticide* use is seen as the best means to protect *crops* against *pests by most farmers in developing countries. It also supports the study by* **Rahman & Chima (2018)** which disclosed that farmers in Nigeria depend highly on the use of pesticides, to the extent where pesticides are treated as substitutes for labour and ploughing services.

Furthermore, this study result of the use of IPM practices (4.3%) which depicted about the least percentage of cases, supports the findings of **Parsa *et al*. (2014)**, where they reported that despite the theoretical prominence and sound principles of integrated pest management, which leads to reduced use of pesticides with better results, IPM continues to suffer poor adoption rates in developing countries (including Nigeria).

The various pest management practices of the maize farming households in this study were grouped into pest management decision categories and the result obtained as indicated by the maize farmers as their main pest management decisions is captured in Figure 1. More than half (58.6%) of the maize farmers indicated that they decided to use chemical control as their main pest management decision with the least number of farmers (4.3%) indicating IPM as their main pest management decision.

Factors that Influence Pest Management Decisions among Maize Farming Households in FCT

Multinomial probit analysis was carried out to determine the factors influencing pest management decisions of maize farming households in the study. Predictor variables used in the analysis were checked for issues of multicollinearity using variable inflation factor (VIF), with all the predictors having a $VIF < 2$ (Mean $VIF = 1.27$), which showed that there was no issue of multicollinearity. The result of the analysis is presented in Table 3. Physical control was used as the reference output category for the dependent variable, pest management decisions of maize farming households in FCT. The result of the analysis showed that the multinomial probit model fits better than an empty model (Wald's Chi-square test, $X^2(21) = 54.90$; $p = 0.0001$) and thus led to the rejection of the null hypotheses.

The variable 'Gender' ($\beta = -1.2262$, $p = 0.002$) was negative and significant for cultural control outcome category, which showed that male maize farmers were less likely than females to prefer or decide on using cultural control measures relative to physical control measures in pest management control. This was expected since males are more inclined or receptive to physical or strenuous activities than females. The variable 'Access to agricultural extension services' ($\beta = 0.9475$, $p = 0.002$) was also significant but positive for the cultural control outcome category, which showed that having access to agricultural extension services increases the preferences or decision of maize farmers towards the use of cultural control measures relative to physical control measures. This was expected since most agricultural extension service programmes tend to promote cultural control measures than physical control activities in pest management.

The variable 'Gender' ($\beta = -0.9657$, $p = 0.012$) was negative and significant for the chemical control outcome category and showed that being a male maize farmer, compared to female, reduces the preference or decision towards using chemical control measures relative to physical control measures in pest management. Again, this was expected as females are more likely to prefer the use of chemical control measures which is less physically demanding than physical control measures in pest management. The variable 'Access to agricultural extension services' ($\beta = 1.0549$, $p < 0.001$) was also highly significant but positive for the chemical control outcome category, which showed that having access to agricultural extension services increases the preferences or decision of maize farmers towards the use of chemical control measures relative to physical control measures. This was expected and similar to the findings of **Alabi *et al.* (2014)** where it was observed that the tendency for smallholder's farmers to use agrochemicals increased with increase in extension services. A review by **Pan *et al.* (2021)** revealed that support and training received from extension services was a positive factor to farmers' pesticide application.

The variable 'Level of education' ($\beta = 0.2170$; $p = 0.096$ at 10% level of significance) was also significant and positive for the chemical control outcome category, which showed that the level of education increases a maize farmer's preference or decision to use chemical control measures relative to physical control measures. This was expected since chemical control measures are considered as improved technology, as adoption or utilization of improved technologies increases with education. The influence of education on the adoption of improved technology had been reported in a study by **Okonji & Awolu (2020)** where it was revealed that educational status of the farmers significantly influenced the adoption of improved maize technology.

The variable 'Age' ($\beta = -0.0491$; $p = 0.088$ at 10% level of significance) was negative and significant for the IPM outcome category, which showed that as age increases, the preferences or decision of maize farmers towards the use of IPM practices relative to physical control measures decreases. This was not expected, and since experience comes with age, it was assumed that the use of IPM practices should increase with age. However, the negative significance associated with age may be due to the lack of technical knowledge and skill of the application and benefits of IPM practices among the older respondents. This result negates the findings of **Das *et al.* (2016)** in a study carried out in District of Narail -

Bangladesh, where farmer's age was found to have a significant positive relationship with use of IPM practices. This difference may be due to the relatively younger population (mean age of 37.87) from their study and differences in geographical location.

The variable 'Access to agricultural extension services' ($\beta = 1.8204$, $p = 0.004$) was positive and significant for IPM outcome category and showed that having access to agricultural extension services increases the preferences or decision of maize farmers towards the use of IPM practices relative to physical control measures. This positive relationship was expected as agricultural extension services tend to promote improved technology. This result is supported by studies from **Mohammadrezaei & Hayati (2015)** and **Rezaei-Moghaddam & Samiei (2019)** where agricultural extension services was found to be the most important factor encouraging the adoption of IPM practices by farmers. On the contrary, the study by **Das *et al.* (2016)** showed no significant relationship of extension contact with IPM practices. The small sample size of 103 respondents may have been responsible for this non-significance in their study.

Finally, for the significant variables, the variable 'level of education' was also positive and significant ($\beta = 0.6622$, $p = 0.004$) for IPM outcome category and showed that level of education increases a maize farmer preference or decision to use IPM practices relative to physical control measures. This was expected and is supported by the studies of **Das *et al.* (2016) and Rezaei-Moghaddam & Samiei (2019)** which showed that educational level had a significant positive relationship with their use of IPM practices.

The variable 'Member of Cooperatives,' though insignificant was expected to be significant especially for the IPM outcome category, since it is assumed that being a member of a cooperative enhances dissemination of information and adoption of appropriate technology. However, this was not the case probably due to the limited knowledge of the importance of IPM practices among members of cooperatives in the study area.

The result of the multinomial probit analysis showed that the significant factors which influenced pest management decisions among maize farming households in the study, were gender, access to agricultural extension services, age and level of education. This result supports the findings of a study conducted by **Melkamu (2018)** on maize farmers in East Showa, Ethiopia, which showed that gender, education, age, extension contact, among others, were significant factors in the use of local pest management practices. The result of this study also supports that of **Alalade *et al*. (2017)** which examined the usage of chemical and biological pests control methods among farmers in Kwara State, Nigeria, and showed that educational level, age, among others, were significant factors in the usage of chemical and biological pest control methods.

Table 3: Result of MNP Analysis for Factors that Influence Pest Management Decisions among Maize Farming Households in the Study Area

MainPMP	Factors	β Coefficient	Std. Err	z	P>z	[95% Conf. Interval] Lower	Upper
Cultural	Gender	-1.226184	0.399587	-3.07	0.002***	-2.00936	-0.443008
Control	Age	0.001323	0.021136	0.06	0.950	-0.0401017	0.0427484
	HHoldSize	0.026498	0.040539	0.65	0.513	-0.0529582	0.1059534
	AccessExt	0.947477	0.298754	3.17	0.002***	0.3619307	1.533023
	AccessCredit	0.225982	0.432151	0.52	0.601	-0.6210194	1.072983
	MemCoop	0.068855	0.304151	0.23	0.821	-0.5272695	0.6649791
	LevelEduc	0.181984	0.142638	1.28	0.202	-0.0975808	0.461549
	_cons	-0.025070	0.840403	-0.03	0.976	-1.672229	1.62209
Chemical	Gender	-0.965712	0.383792	-2.52	0.012**	-1.717933	-0.213492
Control	Age	0.016152	0.019268	0.84	0.402	-0.0216133	0.0539164
	HHoldSize	-0.024336	0.037588	-0.65	0.517	-0.0980084	0.0493355
	AccessExt	1.054938	0.267505	3.94	0.000***	0.5306386	1.579237
	AccessCredit	-0.444391	0.413107	-1.08	0.282	-1.254067	0.3652834
	MemCoop	0.315862	0.277916	1.14	0.256	-0.228843	0.8605687
	LevelEduc	0.217042	0.130224	1.67	0.096*	-0.0381908	0.4722758
	_cons	0.168578	0.791638	0.21	0.831	-1.383004	1.720159
IPM	Gender	-0.284814	0.564424	-0.50	0.614	-1.391064	0.8214365
	Age	-0.049085	0.028773	-1.71	0.088*	-0.1054787	0.0073089
	HHoldSize	-0.028918	0.059253	-0.49	0.626	-0.1450516	0.0872162
	AccessExt	1.820424	0.632609	2.88	0.004***	0.5805329	3.060314
	AccessCredit	-0.434129	0.602677	-0.72	0.471	-1.615354	0.7470949
	MemCoop	0.753883	0.490376	1.54	0.124	-0.2072357	1.715001
	LevelEduc	0.662162	0.227542	2.91	0.004***	0.2161869	1.108136
	_cons	-1.503261	0.876875	-1.71	0.086	-3.221904	0.2153816

Note: Model: Wald $\chi^2(21)$=54.90 and $p = 0.0001$; Outcome MainPMP==Physical Control (Base outcome); Triple asterisk (***), double asterisk and asterisk denote variables significant at 1%, 5% and 10% respectively.

Source: Computed from field data, 2020.

Similarly, the result of this study is similar to that conducted by **Alabi *et al.* (2014)** in Gwagwalada and Kuje Area Councils of the Federal Capital Territory, Nigeria, where they revealed that farmers' decision to use agrochemical inputs increased with age, extension services, education-level and experiences in farming, among others.

CONCLUSIONS AND RECOMMENDATIONS

This study examined the factors influencing pest management decisions among maize farming households in the Federal Capital Territory, Nigeria. The study revealed the use of chemical pesticides as the most carried out pest management practice among the maize farming households. Relatedly, chemical control was also shown to be the main pest management decision of the maize farming households, notwithstanding the obvious negative health and environmental effects associated with the use of chemical substances for pest control. Despite the merits of IPM practices to pest management, IPM was relatively unknown in the study area.

The factors shown to influence pest management decisions of the maize farming households in the study area were gender, access to agricultural extension services, age and level of education. Therefore, to improve pest management decisions of maize farmers in FCT, measures should primarily be targeted at improving the level of education and access to agricultural extension services to the maize farmers. Thus, relevant non-governmental organisations, ministries and agencies in education and agriculture should provide facilities and incentives aimed at promoting and encouraging crop farmers to acquire formal education through adult education programmes in continuing education centres.

Pest management aspects of agricultural extension programmes from relevant agencies should be made more robust while promoting IPM practices over chemical practices due to the enormous merits of IPM practices to the serious negative health and environmental effects of chemical pest management practices. Agricultural extension agents should be well trained on best pest management practices and adequately motivated for enhanced service delivery in boosting pest management decisions of maize farmers in FCT. Input subsidies and the establishment of farmers' field schools by relevant agencies should be provided to promote pest management decisions.

As a limitation to this study, primary data for the research were gathered from three area councils in the Federal Capital Territory of Nigeria. Secondly, the study was limited to the assessment of determinants of pest management decisions of maize farming on the field, and as such pest management decisions on maize storage and transportation were not considered. These were all due to time and financial constraints.

There is need for further research on determinants of factors influencing pest management decisions among maize farming households in other agro-ecological zones of Nigeria. Studies should also be carried out on determinants of pest management decisions in maize storage among farming households in FCT and also on determinants of pest management decisions in other crops such as tuber or vegetable crops. Determinants of risk management associated with pest control among maize farming households is another suggested area for research.

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EVALUATING MEMBERSHIP DURATION IN THE PARTICIPATORY FOREST MANAGEMENT ON LIVELIHOOD IN ETHIOPIA: A GENERALIZED PROPENSITY SCORE APPROACH

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ABSTRACT

Research background: Participatory Forest Management program (PFMP) is initiated to manage forest resources and promote household participation to enhance their livelihood. In contrast, the long-term evaluation of many programs' timing remains low attention. Thus, it is vital to measure livelihood impacts on membership duration associated with the PFM program in Ethiopian farm households
Purpose of the article: To evaluate the impact of membership duration in participatory forest management on livelihoods of program participating households in south-western Ethiopia. The results of the program's periodic assessment data were analysed on the long-term effect of the activities of forest management members.
Methods: The study applied the generalized propensity score method. The research depends on cross-sectional survey data collected in mid-2018 from 267 farm households from Sheka and Kafa zones of south-western Ethiopia. The procedure matched families with similar covariates with different years of membership duration in the participatory forest management program. The technique was used members' annual per capita expenditure as an indicator outcome variable for measuring rural livelihood.
Findings, value-added & novelty: Impacts studies of PFMP on heterogeneous effects across different groups of membership duration are scarce, and there is a research gap on how membership duration affects outcomes. Our study addresses this gap by measuring the long-term evaluation of program outcomes and their impacts on the participatory member households. Furthermore, the result revealed that the program's effects were initially low but positively affected when approaching an optimum year of membership dose. The program's optimal duration of the membership dose was 11-12 years, and 4263.75 birrs were the optimal level of yearly household per capita consumption spending.
Recommendation: The results recommend more work on the participating household members by encouraging new forest-related income sources and integrating the socio-economic network more closely with the forest's ecosystem services. Although the relationship among participating members of households' longevity and income is substantial, the program has been focused on the medium and longer duration of the forest program participating.

Keywords: membership duration; participatory forest management; generalized propensity score; dose-response function; consumption expenditure
JEL Codes: Q23; D02; C01; C13; C56

INTRODUCTION

Participatory Forest Management (PFM) was brought to Ethiopia in the mid-Nineties, like in many other African countries, with the help of worldwide NGOs and bilateral businesses **(Temesgen *et al.*, 2007)**. The development of the PFM program in Ethiopia has unexpectedly extended and transferred the control responsibilities of more than 1,000,000 hectares of forests, almost one-third of the dense forests, to organized local groups. In Southern Nations, Nationalities, and People's Regional State (SNNPRS) of Ethiopia, the introduction and implementation of the PFM program started with government resources following the inception of the Energy Access Biomass Supply Management Project in 2003, with a budget obtained from the World Bank on a loan basis, government treasury funds, and contribution by the local people in the form of labour. The project started operating in nine *woredas* of the region, which have relatively more intact natural forests. These include Arora woreda in Sidama zone (eastern part of the region) and Bita, Gesha and Gate woredas in Kaffa zone, Masha and Andrache woredas in the Sheka Zone, and Sheko, Shewa Bench, and Bench (currently North Bench) woredas in Benchmaji zone **(Kelbessa & Destoop, 2007).**

PFMP is commonly used to manage forest resources worldwide to promote cooperation and reduce poverty **(Adam & Eltayeb, 2016**). Similarly, the other study supported the idea that natural forests have an essential role in the financial improvement of forest communities **(Mislimshoeva *et al*., 2016).** Local people's involvement in forest conservation might range from simple community engagement to a complete transfer of conservation and management authority to the locals **(Okumu *et al*., 2020)).** PFMP is a technique to accomplish practical backwoods by empowering timberland ensured regions and forest assets by the networks living in and around the assistance. PFMP is recommended to develop other food security and reduce poverty in developing countries **(Kelley & Scoones, 2000).** In this way, it may contribute to achieving the three sustainable development Goals (SDGs). As community members, particularly in developing countries including Ethiopia, rely primarily on the immediate utilization of natural resources, including woodlands, achieving the three SDGs will influence the conservation, reasonable use, and management of the forest assets. For instance, **Yemiru *et al.* (2010)** discovered that forests contributed 23.53 percent of the average household income in south-eastern Ethiopia. **Melaku *et al.* (2014)** found that forests contributed 47 percent of yearly household income in south-western Ethiopia depending on income quintile.

The long-term contributions of PFMP were improved by designing forest management development approaches, an understanding of relationships among resource use patterns is critical. Particularly the Sheka and Kaffa forests are essential for the conservation of Afromontane forest, and the area also includes bamboo thickets, wetlands, and the agricultural regions. These forests provide vital products in the local communities, including forest and non-forest products, such as medicinal plants, honey, and wild fruits. The communities are committed to maintaining the longevity of the ecosystem, which includes practicing ecologically sustainable agriculture **(Ishwaran *et al.*, 2008).**

PFMP is an instrument to protect forests and enhance the livelihoods of communities who use and benefit from it in the process. FM was meant to avert deforestation's persistent problems and deliver better social and economic outcomes than the former centralized command-and-control resource management approaches **(Ayana *et al*., 2015)**. In other words, the program designed twofold approaches to sustainable forest management. The first is establishing community-level forest management systems and promoting forest-based livelihoods, and the second is introducing and supporting other non-forest-based alternative livelihoods **(Temesgen *et al.*, 2007)**. Many investigations have shown that PFMP contributes to improving forest protection (e.g., **Siraj *et al.*, 2018; Kadir *et al.*, 2018)**, but the welfare impact of household involvement in PFMP is currently unclear and remains inadequately comprehended despite their significance for the long-term economic viability of the concept. In particular, PFMP imposes new prohibitive guidelines and regulations on woodland-related job opportunities, basically through collecting limitations **(Larson & Pulhin, 2012),** which may decrease forest-based earnings (**Schreckenberg & Luttrell, 2009**). PFMP programs introduced income-generating activities by providing value to forests (for example, tourism activities), continuing to develop alternatives of forest products and revenue (for example, woodlots), or paying for losses **(Gobeze *et al.*, 2009).** However, the government assistance ramifications of these additional advantages or pay likewise remain inadequately comprehended.

Therefore, this study focused on local communities of the PFMP contribution in evaluating food security and the average total annual household income, focusing on estimating the effects of PFMP's significant livelihood indicators outcomes in Sheka and Kafa forests. This study evaluated the impact of membership duration in the PFM program in south-western Ethiopia. We tested whether the duration of membership in the PFM program has a significant livelihood impact or not. The longer the exposure of members to the program would yield to raises income (in terms of Annual Per capita expenditure) among rural membership households. Moreover, cumulative effects such as membership duration and accumulation of knowledge require the passage of time; this implies that longer the program exposure would yield more significant gains. To handle these two objectives in measuring the impact or evaluation of the PFM program, we used GPS application in simulating PFMP impacts on random experiment process with consideration PFMP effects on heterogeneous effects in membership individuals.

Previous research studies provide an excellent foundation for the research on the topic, although they have some limitations that require further analysis. First, previous studies focused on the benefits and costs of forests to communities through PFMP management are based on qualitative analysis that considers forest condition and participant income **(Bekele *et al*., 2004; Takahashi & Todo, 2012)**. They did not provide clear pictures regarding the overall impact of PFMP on local livelihoods and other outcomes. Second, many previous studies relied on average differences between PFMP participants and non-participant households without accounting for potentially confounding pre-PFMP differences (e.g., **Gobeze *et al*., 2009**; **Maharjan *et al.*, 2009**). Even though some African and Ethiopian studies considered overcoming pre-PFMP differences **(Ameha *et al.*, 2014b; Mutheu & Friss, 2016),** they assumed individual-level homogeneity of matched PFMP participants in non-participant households. Non-participated households of PFMPs also live close to the forests, and their livelihoods have a strong relationship with forests. It is impossible to get comparison groups that are not influenced by forests. This circumstance may result in sample selection bias. To overcome this limitation, the researchers assessed the effects of PFMP by estimating the continuous dose-response function that relates to each dose value, i.e., years of membership participation intensities to the individual post-treatment covariate using generalized propensity score matching. Thus, varying duration of membership in the program might lead to heterogeneous responses to the estimation result of program outcome and measures heterogeneity in impact among members in PFMP.

In designing community-based forest management approaches, an understanding of the It is critical to understand the relationships between resource use patterns. Cases in which resource users are discriminated against are of specific interest. Diverse stakeholders with various interests and forest dependency vary across households **(Adhikari *et al.*, 2004; Wehn *et al*., 2019; Masozera & Alavalapati, 2005)**. Community-managed forests are particularly susceptible to such information flow gaps because it requires a broad approach beyond the forest ecosystem and includes policymakers and local people. To meet the criteria for the sustainable use of forests and the development of participatory forestry, policymakers, planners, and project designers need to have information within the context of the dynamic interaction between heterogeneity of impacts.

The study at hand also contributed to the areas of study in estimating the impacts of PFMP. However, the research methods and findings will have broader relevance to help other forest conservation areas include community values, involvement, and management perceptions. This study aims to quantify PFM program impacts on outcome indicators of livelihoods, i.e., annual households' per-capita consumption expenditure. The primary research questions to be addressed in this study include: Is there a link between the duration of PFMP membership and the consumption expenditures of rural farm households in the Sheka and Kafa participatory forests? If yes, what is the heterogeneous nature of their relationship? To what extent do families participating in PFMP have improved their livelihoods? What are the optimal levels of Membership duration at which its benefits are maximized?

The article's overall aim was to assess the impact of participatory forest management on household livelihood in rural southwestern Ethiopia's Sheka and Kafa forests. The study's specific objectives are: To measure the Impact of PFMP on the livelihoods of the participating families; To determine the heterogeneous nature of the involvement and estimate optimal levels of Membership duration at which its benefits are capitalized on membership in the Participatory Forest Management in Sheka and Kaffa zones.

LITERATURE REVIEW

Impacts of PFMP on livelihoods

An expansion has been underway in Ethiopia, escaping a variety of forest management arrangements that could benefit from the contributions of families in dense forest areas and the potential benefits of the forests **(Ameha *et al.*, 2014a).** Based on the stages and social foundations of community forest management, various studies have discussed the impact and benefit of different forestry administration (PFM) programs. One of these studies, based on the dependence on natural resources **(Gatiso, 2017),** shows that rural Ethiopia's participatory forest plays an essential role in the livelihoods of society and indicates that the local community is more likely to contribute to the forestry administration. Similarly, **Tesfaye *et al.* (2011)** noted that the local community's forest income is a good source of income that allows low-income families to enhance their living conditions. However, gain from the forest program was limited by market distance, age of the household head, and geographical constraints

Mutheu & Friss (2016) studied the impact evaluation of the livelihood outcomes of PFMP in Kenya. It does so by comparing members and non-members of community forestry associations (CFA) among communities residing near the Eburu and Sururu Forest Reserves. Mainly, they examined the policy of PFMP as it unfolded in practice on the ground and sought to evaluate its impacts through matching of CFA and non-CFA member (NCFA) households based on recall data to generate estimates of effects on household income. Results show that CFA member households had higher total family, forest, beekeeping, and tree seedling incomes than non-CFA households. Overall livelihood impacts were driven more by differential forest-related labour and market opportunities supported by NGOs and donor institutions than by differential access to forest products. However, there were indications that poor NCFA households experienced reduced relative forest incomes following the increased intensity of forest patrolling.

Ameha *et al.* (2014b) studied the impact evaluation of the livelihood outcomes of PFMP in Ethiopia. This study was conducted in two forest provinces in Ethiopia. The paper analyses how PFMP affects members of groups in the forest management program collects income data from 635 members using random sampling. Results from the propensity score matching revealed that when members' gross income in Ethiopia's forest management program is calculated, it is less diverse than non-member resources in the program. Notably, In Dodola, where commercial timber harvesting is permitted, the implementation of PFMP means that FUGs now have more livestock assets and forest income than non-members. However, the average total income and expenditure for members and non-members were not statistically different. According to the Chilimo site, the introduction of PFMP means that FUG members have lower real incomes and assets than non-members. Research findings recommend revising the PFMP scale-up approaches in Ethiopia, which currently allow FUGs only subsistence use from forest resources. It should amend the provision to be reproductive and participants to benefit from the management.

DATA AND METHODS

Study Areas

This study was conducted in Sheka and Kaffa zones of Southern Nations, Nationalities, and People's Regional State (SNNPRS) of Ethiopia, where the PFMP project was implemented. Sheka zone is located in the SNNPRS, southwest part of Ethiopia. Sheka zone covers 2387.54 km^2 [(Sheka zone Finance and Economy Development Department (SZFEDD, 2012). The administrative center of the Sheka zone is located 676km southwest of Addis Abeba. Geographically, the area lies between 7°24' - 7°52' N latitude and 35°13' - 35°35' E longitude and consists of three districts, namely the Masha, Andracha, and Yeki. The zone is bordered to the north by Oromia Regional State, the west by Gambella Regional State, the east by Kaffa Zone, and the south by Bench Maji Zone. In the two districts of Masha and Yeki(town name, Teppi), there are 45 rural and two urban Kebeles (Kebele- a minor authoritative grouping in Ethiopia).

Kaffa zone is located in SNNPRS, the most ethnically and linguistically diverse region of Ethiopia. Bonga is the administrative town of the location situated 450 km away from Addis Ababa. The zone is mainly covered with evergreen montane forest and is part of the Eastern Afromontane Biodiversity Hotspot. According to the 2007 census, the area's total population is 858,600, with a population density of 90 persons per square kilometer. Its altitude ranges from 500 to 3500 m.a.s.l (above sea level) with the mean annual rainfall and temperature ranging from 1001 - 2200mm and 10.1 - 27.5°C, respectively. The agro-ecological condition of the Kaffa zone is very suitable for growing coffee, tea, spices, and other crops. The study areas in the PFMP project are located in the south-western part of Ethiopia in the SNNPRS and focus on four woredas: Anderacha and Masha woredas in Sheka Administrative zone, Gimbo, and Chena woreda in the Kaffa administrative zone.

Sampling Techniques and Sample size

The study mainly used a structured survey questionnaire to collect cross-sectional data on a face-to-face household interview in November and December 2018. The study applied multi-stage sampling techniques. In the first stage of the sampling procedure, four *Woredas* from two zones were selected based on the PFMP targeted and actively participating Woredas; Masha and Andracha from Sheka zone; and Gimbo and Chena from the Kafa zone. In the second stage, the selection of Kebeles from respective Woredas; gives all Kebeles in the survey an equal probability of being selected as a sample. Three from Masha, two from Andracha, three from Gimbo, and two Kebeles from Chena woreda were selected based on these criteria. Finally, 267 households were randomly selected based on PFMP participated household head lists in the sample *Kebeles*.

Data types and data gathering

A questionnaire was used to collect relevant data. The questionnaire encompassed demographic, socio-economic, institutional services, social capital, networking, and forest management issues. Different questions were posed to informants based on their professions and their responsibilities. This allows us to recognize better the problems raised and triangulate the answers given by respondents - critical informant interviews with government officials and development agents in each sample kebele of Sheka and Kaffa zones. The discussion with experts focused on the different livelihood activities and environmental income of participant households, knowledge on forest management, and their perception of forest conservation.

Analytical Methods

The econometric model, generalized propensity score matching (GPS), is the potential outcome approach that **Hirano & Imbens (2004)** developed and is now widely used in different interventions evaluation literature. Suppose a representative sample of elements from a high proportion, adjusted by $i = 1, \ldots\ldots N$, for each unit i, and there is a set of potential outcomes referred to $\{Y_i(t)\}\, for\ t \epsilon T$ for each unit I under the level of treatment t. A group of possible results $Y_i(t)$ For t known as the causal inference of a single – dose-response function (DRF). PFMP participation with varying length of membership doses (years of PFMP membership in a household) is in the T interval $[t_0, t_1]$, with $t_0 > 0$ **(Hirano & Imbens, 2004).**

The primary goal is to calculate the average dose-response function (ADRF) $\mu(t) = [Y_i(t)]$ denotes the mean livelihood indicators of the outcome across all members of PFMP participation levels. $Y_i(t)$ is a livelihood indicator of annual household per-capita consumption expenditure for a household member of the PFM program.

The observable variables for each univariate vector of covariates, the level of the treatment that unit i receives, and the potential outcome corresponding to the treatment level $Y_i = Y_i(T_i)$. Because of the GPS effect of the process on ADRF and marginal treatment tasks for household members of the PFM program, families who did not participate in the PFMP are not included in the model.

Hirano & Imbens's (2004) critical assumption generalizes the unconfoundedness and Balancing belongings assumptions similar to the binary treatment **Rosenbaum & Rubin (1983)** made to the continuous impact study. It asserts that once observable elements been controlled for, X_i, any residual variation in treatment response T_i Throughout units is independent of possible effects outcomes $Y_i(t)$ (Equation 1).

$$Y_i(t) \perp T_i / X_i \text{for all } t \in T \qquad (1)$$

The random variable treatment T_i is assumed to be conditionally independents of random effect, measured at an arbitrary treatment level t. Therefore, the assumption of weak unconfounded in the average dose-response function is obtained by estimating intermediate outcomes at different levels of treatment. Calling $r(t, x) = f_{T/X}(t/x)$ the conditional density of the continuous treatment given the covariates in $R_i = r(T_i, X_i)$.

GPS has a balancing property test for treatments within strata with the same value of $\mathfrak{r}(\mathrm{t_i}, \mathcal{X})$ the probability that $(T = t)$ does not depend on the value of $\mathcal{X}$, i.e., the GPS has the property that $X \perp \{T = \mathrm{t}_i\} / \mathfrak{r}(\mathrm{t_i}, \mathcal{X})$.

Given this result, applying the GPS to remove bias caused by covariate variations in two steps. The first stage is to calculate the outcome's conditional expectation as a function scalar variable, the treatment level T and the GPS R., as expressed in $\beta(\mathrm{t}, \mathfrak{r}) = \mathrm{E}[Y/\mathrm{T} = \mathrm{t}, \mathcal{R} = \mathfrak{r}]$ The second stage is to estimate the DRF averaging the conditional expectation function over the GPS at that specific level of the treatment (Equation 2).

$$\mu(\mathrm{t}) = \mathrm{E}\left[\beta\left(\mathrm{t}, \mathfrak{r}(\mathrm{t}, \mathcal{X})\right)\right] \mathrm{t} \,\forall\, \mathrm{T} \qquad (2)$$

As a result, estimating intermediate outcomes at different levels of treatment yields the assumption of weak unconfoundedness in the average dose-response function. Thus, the parameters of the treatment duration function i.e.β_0 ,β_1 and $\{ Y_i(t)\}\, for\ \varepsilon\, T$ (conditional distribution of membership duration) are estimated using maximum likelihood or ordinary least squares regression according to Equation (3).

$$T_i/\chi_i \sim N[\beta_0 + \beta_1 \mathcal{X}_i, \delta^2] \qquad (3)$$

Before moving on to step two, GPS can be estimated after evaluating the model of the treatment component in Equation (3). GPS can be calculated in Equation (4).

$$\hat{R}_i = \frac{1}{\sqrt{2\pi\delta^2}} \exp\left[-\frac{1}{2\delta^2}\left(T_i - \hat{\beta}_0 - \hat{\beta}_0' X_i\right)^2\right] \qquad (4)$$

The conditional is determined in the second stage. Expected function of the outcome (Y_i), given modeled as a flexible function (polynomial approximation) of experimental treatment (T_i) and estimated GPS (R_i), for the analytical approach, uses the quadratic approximation followed in Equation (5).

$$E([Y_i/T_i, \hat{\mathcal{R}}_i]) = \alpha_0 + \alpha_1 T_i + \alpha_2 T_i^{\,2} + \alpha_3 \hat{\mathcal{R}}_i + \alpha_4 \hat{\mathcal{R}}_i^{\,2} + \alpha_5 T_i \hat{\mathcal{R}}_i \qquad (5)$$

As a result, the study's outcome variable is continuous; g was assessed using the ordinary least squares (OLS) regression model. Lastly, the average response function at a given treatment t value was evaluated by taking the mean (estimated) results for each individual of observed treatment (T_i) and estimated GPS, $\hat{R}_i$ is used.

Given the estimated parameters in the second step, we estimate the average dose-response function at a particular value of the treatment t Equation (6).

$$\mu(t) = E[\hat{Y}(t)] = \frac{1}{N}\sum_{i=1}^{N} g^{-1}[\hat{\alpha}_0 + \hat{\alpha}_1.t + \hat{\alpha}_2.t^2 + \hat{\alpha}_3.\hat{r}(t, \chi_i) + \hat{\alpha}_4.\hat{r}(t, \chi_i)^2 + \hat{\alpha}_5.t.\hat{r}(t, \chi_i)] \qquad (6)$$

Accordingly, the GPS evaluation findings are presented graphically, showing dose-response relation and marginal impact capabilities.

Definition of Outcome, Treatment, and Explanatory Variables

Once the analytical procedure of the study and its requirements are known, it is necessary to identify the potential outcome, treatment, and explanatory variables used in the model. Combinations of socio-economic and demographic factors were used to explain households' membership duration in the PFMP and the outcomes in terms of household wellbeing indicators; the result, treatment, and explanatory variables were used in the GPS estimation are defined as follows.

Outcome Variable

Household per capita consumption expenditure (HPCExp): A continuous outcome variable referring to households' yearly consumption expenditure expressed in Birr. Our interest is to investigate membership duration in the PFMP or dose (treatment) in rural households. Empirical studies indicate that consumption expenditure fluctuates less than income in the short run and provides information over the consumption bundle that fits within the household's budget **(Skoufias & Olivieri, 2013, Haddad & Ahmed, 2003).** As a result, we use per capita consumption expenditure as the key outcome variable in measuring a household's livelihood. The robustness of inference was quantified by included three additional outcome variables. These outcome variables are:

- Income from non-timber forest products: (IncmNTFP). This variable refers to annual household income from non-timber forest products measured in Birr.
- Income from livestock production (IncmLivstk). This variable refers to annual household income measured in Birr.
- Income from crop production (IncmCrop): This variable refers to annual household income measured in Birr.

Treatment Variable

Membership Duration (MDurn): Duration of membership to PFMP in years is the treatment variable used in the GPS estimation is a continuous variable. Participants were asked to answer the question: "For how many years did you participate and stayed period on average in the PFMP?" These reactions were averaged and used as the variable of membership duration. The duration was divided into three categories: less than or equal to six years was considered shorter, while longer than six and less than nine years was deemed medium, and longer than or similar to nine years was defined as longer membership duration. We discard observations with treatment duration two and below two years; since such short durations arguably do not imply a severe effect on outcome variables. Durations above 12 years are also discarded since only very few observations are available.

Explanatory Variables

The explanatory variables expected to have an association level with participation in the PFMP are presented in Table 1. Hence, the demographic and socio-economic factors which are selected based on theoretical background and related literature are defined.

RESULTS AND DISCUSSION

Demographic, socio-economic, and institutional characteristics

A summary of the sampled households' demographic, socio-economic, and institutional characteristics was provided in Table 2. Disaggregating whole sample households into three different years of membership duration, the member groups were categorized into three equal portions at the 30th and 70th percentiles, approximately dividing the sample households into three similar groups **(Hirano & Imbens, 2004; Kluve *et al.*, 2007).** Accordingly, Membership duration ≤ 6 years as shorter; 6 < Membership duration < 9 years as medium and ≥ nine as longer membership duration, and it was observed that 34.33 percent, 33.83 percent, and 31.72 percent of the sample households fall into the shorter, medium, and more extended years, respectively.

Table 2 presents summary statistics of the outcome variables and the covariates for the whole sample and the three sub-samples households, i.e., shorter duration, Medium level of duration, and longer duration. We were looking at the entire model. The average age of the participant households was 42.76 years. The average age in shorter, medium and more extended duration categories is 41.47, 42.51, and 44.32, respectively. Regarding family size, sample households in the shorter, medium, and long years of membership categories had 5.29, 5.85, and 6.25 family sizes, respectively. Furthermore, the F-test result shows that the difference among the three membership categories in family size was statistically significant at the 5% probability level.

Most of the respondents in the group of longer membership duration are old and had many family labourers than more recently joined membership households. Due to higher consumption, larger family sizes had a higher demand for forest products.

Further, livestock holding in TLU for medium and longer treatment duration were the lowest and the highest, respectively. According to the F- test result, the difference is significant at the 5% probability level. The results may further imply that participation as membership in the program gets grass and forage availability for their livestock animals. Furthermore, according to the survey result, the majority of the sample households, on average, had four years of education in study areas.

The result shows that households who are members of the shorter, medium, and long years of duration on average travel to the nearest market in walking times are long distance to the PFMP forest points was observed for a shorter period of membership households. In contrast, the short length was recorded for a longer duration of membership households. Based on walking minutes, the result indicates that early entry membership households are located about 25 minutes closer to PFMP forests. The development might be related to the fact that household membership duration is highly forest-dependent, especially indigenous people near forest areas where forest product availability is critical. Regarding sample households who are groups in shorter, medium, and longer duration of membership categories had, on average, travelled 1.92, 3.3, and 5.15 km to the nearest main road. The difference was statistically significant at a 1% probability level. Other variables have statistically insignificant variances in subgroups of membership households. These results may indicate that some pre-treatment variables have not been associated with participation.

Table 1: Description of explanatory variables

Variable	Variable description	Measurement	Sign
Age	Age of the household head	Years	-
Sex	Sex of household head	Dummy(1=male;0=female)	+
Family size	Number of individuals in the HHS	Number	+
Land size	Landholding size in hectares	Hectare	+
Livestock holding	Livestock owned	TLU	+
Education level	Education level of household head	Years	+
Off/non-farm income	Off and non-farm income	ETB	+/-
Market distance	Distance to the nearest market	Minutes	-
PFMP distance	Distance to the PFMP forest	Minutes	-

Table 2: Demographic characteristics of member households

	Full Sample	Shorter	Medium	Longer	F-test
Continuous variables					
Age	42.76	41.47	42.51	44.32	2.26
Family size	5.80	5.29	5.85	6.28	6.95**
Land size	2.37	2.39	2.64	2.34	2.21
Livestock Asset (TLU)	10.61	10.7	11.4	12.3	7.5**
Education	4.36	3.95	4.37	4.23	1.52
Off/Non-farm	0.23	0.27	0.20	0.22	0.65
Dist._mkt(nearest)	17.2	16.96	21.27	15.4	6.908**
Distance from PFM forest	30.66	36.054	30.09	25.85	7.3***
Outcome Variables					
HPCexp	2895.71	2146.97	2796.68	3743.47	63.18***
IncmNTFP	20615.06	17580.13	20525.87	23739.17	8.31**
IncmCrop	17643.07	16077.99	17607.64	19243.57	8.58**
IncmLivstk	6871.6885	5860.045	6841.955	7913.06	7.31**
No of observations	267	92	90	85	

Table 3: Estimated effects of treatment duration on consumption expenditure

Variables	OLS estimate	Std. Err.	t-value
Treatment duration(G-1)	495.16 ***	79.63	6.22
Treatment duration(G-2)	402.38***	50.68	7.94
Treatment duration(G-3)	384.19***	37.32	10.29
Constant	-219.21	377.73	-0.58
Number of observation	267		

An outcome variable among different categories of the treatment duration (Table 2) shows that the annual household per-capita consumption expenditure is relatively higher in the medium and longer membership duration category level than the shorter membership duration category. The consumption expenditure in the more extended membership duration level is 3743.47 birr.

In line with the primary outcome variables, the study used three additional outcome variables to quantify the robustness, i.e., income from non-timber forest products, crop production, and livestock. The income share from non-timber forest products in the more extended membership duration is 23739.17 birr. In medium duration, about 20525.87 birrs., results reveal that the impacts of PFMP increase with the length of membership duration. It implies that members of longer duration have higher returns on their contribution than members of shorter membership duration households. There could be two explanations for these findings. Firstly, longer membership duration household's practices yield technologies management, which may improve the forest conditions relative to recently entered member's households **(Pokharel, 2012)**. Secondly, longer membership duration households harvest large quantities of harvestable non-timber forest products, and the amount of harvested non-timber forest products is directly linked with the household benefits. In general, the effect of the entry rate concerning continuous years of membership duration in the program was firmly incorporated with additional income obtained from forests. Their involvement may have made them more competitive and generated more benefits from forests.

Effects of Treatment Duration on Consumption Expenditure

Before presenting the GPS model results, we first explore the relationship between annual per-capita consumption expenditure and the duration of treatment (household membership duration) using correlation and regression analysis. The correlation between variables specifies that as one variable changes in value, the other variable tends to change in a specific direction. Understanding that relationship is helpful because we can use the value of one variable to predict the value of the other variable. For this study, household membership duration and consumption expenditure are correlated—as membership duration increases, per-capita consumption expenditure is also likely to increase. Therefore, if we observe an individual who early entered the program and participated for longer years, we can predict that his per capita consumption expenditure is also above the average households who have recently joined the program.

The correlation between membership duration density (dose in treatment duration) and household per capita consumption expenditure seems optimistic with Pearson's correlation of r =0.56. Still, in the square of treatment duration, a cubic form of treatment duration and the fourth power of treatment duration increases with Pearson's correlation coefficient, r = 0.593, r = 0.640, r= 0.695, respectively. Positive coefficients show that when the value of the membership duration increases, the per capita consumption expenditure tends to increase. Again, the positive relationships produce an upward slope on a scatter plot (Figure 1). These results assume a linear relationship between the treatment (membership duration density) and the outcome variable. They do not indicate any causality under the situation of causal inference correlation does not show causation illustration of causal inferences based on observational data we applied GPS model.

Table 3 shows the estimated effects of treatment duration on consumption expenditure investigates the relationship between consumption expenditure levels after entering the program and the treatment duration. There are many situations where there could be non-linear relationships of the explanatory variable on the outcome. We want to examine how much membership duration affects consumption expenditure in our data set. We were estimating the members' level of consumption expenditures (HPCexp), and membership duration (MDurn) has a typical linear, and quadratic effect in farm households are as follows:

The estimated equations resulting from the linear regression line understates the effects of staying for shorter years of membership duration. The trend line slope is lower than the general slope and would overstate the impact of membership duration for higher values of membership duration. The alternative models that could better fit the data are the square of treatment duration and spline function. Square of treatment analysis suggests that longer membership duration leads to more significant consumption expenditure. (Figure 1).

For each value of the membership duration group, the implications of the independent variables on the outcome would be different.; we can apply a spline function. We allow membership duration have a different linear effect at different levels of membership duration categories. Thus, we can estimate the separate marginal impact of "membership duration of ≤ 6 years", "between 6 and 9 years," and (9 ≤ duration ≤ 12 years).

The regression estimates show that there is a positive relationship between per-capita consumption expenditure and membership duration, positive regression results between levels of consumption expenditure and treatment duration are more considerable, and the explanatory power of the treatment is high ($\mathcal{R}^2 = 0.57$), these suggest that the impact of the treatment duration on per-capita consumption expenditure is high or significant. However, regression estimates analysis such as OLS has a higher risk of misspecifiying the model of making comparisons between an only observation, which could bias the estimations. Generalized propensity score approaches can improve these potential problems to some extent.

Estimation of Generalized Propensity score (GPS)

Given the identified covariates, the conditional distributions of membership duration were estimated using Equation (1) and presented in Table 5. Before evaluating GPS, the goodness-of-fit tests for normality were conducted. The treatment variable, the membership duration of participating households in the PFMP after entry into the program, statistics were approximately normally distributed. The Kolmogorov-Smirnov is used to check the null hypothesis that a data set comes from a normal distribution. The Kolmogorov Smirnov test at information with degree normality is satisfied at the 0.05 level of freedom parameter (Table 4). Based on normality tests, the distributions of membership duration among the sample households were graphically depicted, and the distributions covered in ranges of exposure intensities are distributed normally (Figure 2).

Balance of covariates test

Here, after assessing the balance of covariates test, the GPS property of credit was examined. The balancing tests' results within each year of membership duration (dose) interval were reported in Table 6. The GPS's balancing property was tested by comparing the conditional mean of the pre-treatment factors. The GPS is not diverse between families belonging to a specific treatment of members group and households belonging to all other treatment members' groups **(Rosenbaum & Rubin, 1983).**

The balancing property of GPS was evaluated by cutting the length of membership data at the 30th and 70th percentiles, as the procedure suggested by **Hirano & Imbens (2004).** Accordingly, covariates distributions of the study area were analysed among three groups. For categories group one (members with a length of membership ≤ 6); group two (6< households with the size of membership (dose) < 9) and group three (9 ≤ households with the length of membership (dose) ≤ 12) and families in the first, the second and the third membership groups were 92, 90 and 85, respectively.

The balance for each group variable was examined by testing whether the average in one of the three treatment groups was different from the average in the other two treatment groups combined **(Bekele *et al.*, 2018**). In Table 6, the t-test values for each group variable were reported. The balance findings reveal that 10 (13) of 87% of t-statistics are less than 1.96 (1.65) in value. Out of 12 covariates, the t-values of 11(12) covariates were less than 1.96 (1.645) in total value, which shows balances. Therefore, stopping here and estimating the DRF in this analysis, balancing the covariates was done without adjusting GPS.

Figure 1: The relationship between consumption expenditure linear, prediction, and duration

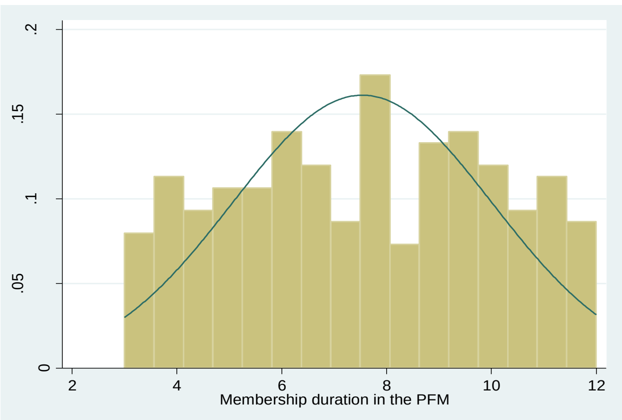

Figure 2: Distribution of estimated membership duration among sample households

Table 4: Normality test of the distributions

Smaller group	D	P-value	Corrected
res_etreat:	0.0527	0.227	
Cumulative:	-0.0826	0.026	
Combined K-S:	0.0826	0.052	0.044

Note: Test of normality would be statistically significant at 0.05 significance level

Table 5: GPS results: Duration of membership intensity on covariates

Variables	Coef.	Std err	Z-value
Age of the household head	0.082***	0.23	3.63
Sex of household head	- 0.23	0.35	- 0..65
Family size	0.37***	0.09	3.75
Education	-0.067	0.911	- 0.74
Off farm income	-0.104	0.301	-0.35
Livestock	0.13*	0.49	2.63
Nearest_pfm	-0.025***	0.006	-3.68
Nearst_mkt	-0.024***	0.007	-3.25
Land size	1.58***	0.37	4.29
Marital status	0.039	0.198	0.2
Age square	-0.005***	0.0012	- 3.76
Age cube	0.001***	0.000015	3.46
Livestock owned square	-0.068	0.262	-1.18
Livestock owned cube	0.002	0.003	0.6
Household size square	0.217	0.262	0.83
Household size cube	-0.067	0.015	-0.89
Education square	0.052	0.043	1.21
Education cube	-0.002	.002	0.9

Note: ***, **, * shows significance levels at 1%, 5%, and 10%, respectively
Source: researchers' calculations

Table 6: Balancing check of Covariates

Variables	T(3,6)	T(6.1,9)	(9.1, 12)
Age of the household head	0.623	0.314	-0.287
Sex of household head	0.621	-1.149	-0.830
Education	0.773	-1.452	0.448
Family size	0.487	-0.322	-0.088
Livestock owned	-0.525	0.141	1.063
Nearst_pfm	-0.639	0.111	0.468
Nearst mkt_	-0.516	-0.221	1.239
Land Size	1.147	-0.128	-2.645
Marital Status	-0.760	1.201	0.639
Off farm/Non-Farm income	-1.379	0.994	-0.652
Age_square	0.890	-2.428	2.026
Age_cube	1.101	-2.690	2.133
Eduyears_square	0.738	-1.868	0.847
Eduyears_cube	0.744	-1.993	0.993
Famuly size _square	0.663	-0.780	0.325
Famuly size _cube	0.731	-1.033	0.603
Livestock owned _square	-0.241	0.219	0.793
Livestock owned _cube	-0.122	0.459	0.499

Common support condition

Common support conditions for the membership duration were tested; we divided the sample into three groups as we have done above when examining balancing covariate tests. Then we estimate the GPS of the entire selection at the median treatment duration of group 1, i.e., 4.7 years. After that, we plot the distribution evaluated GPS for group 1 versus the rest of the sample in the exact figure shown in Figure 3. We then assess the GPS at the median treatment levels of the second and third groups and repeat the similar course of action for the distributions. Finally, for the data sets, each GPS set of three common support domains are depicted in (Table 7) and Figure 3. Consequently, the overall common support region would examine and trim out six from group two 19 from group three, then the common support condition is satisfied in our data.

Impact of PFMP on households' per capita consumption expenditure

For the study area, following the confirmation of balancing property of the respective estimated GPS, per capita expenditure of anticipation of the households was estimated as a function of two scalar variables (membership duration and the GPS) and their interaction via Equation (5) (Table 8). In Table 8, the outcome variable household per capita expenditure (HPCExp) is a continuous variable, and the DRF at membership duration, t, is estimated through the polynomial of order two regression Equation (7)

$$\mathrm{H}PCExp(t) = \alpha_0 + \beta_1 \mathrm{MDurn_i} + \beta_2 (MDurn_i)^2 + \beta_3 GPS_i + \beta_4 (GPS_i)^2 + (MDurn_i)(GPS_i) + \varepsilon_i \qquad (7)$$

Note that the result obtained has two purposes but does not have to render causal implications to develop causal inference – to generate average DRF and to re-assess whether the covariates introduce bias **(Hirano & Imbens, 2004; Liu & Florax, 2014).**

The final step of impact analysis using the GPS method is measuring the mean DRF, which shows inferences. The moderate impact of membership duration on household per capita consumption expenditure at a particular year of membership dose was estimated using Equation (6). The average potential outcome was assessed based on **Hirano & Imbens (2004)** on ten values of duration 3, 4, 5… 12. For the study area, the DRF at membership duration t, an average membership duration effect t was evaluated as E [HCPexp (t)] and depicted. The solid line illustrates the estimated results of the dose-response function (mean membership duration effect); lines with a splash are 95% upper and bottom bound distances of confidence acquired through bootstrapping. However, it does not sense to discuss the graph's dashed lines as a causal relationship between membership length and consumption expenditure because of a pretty large confidence band (Figure 4) that emanates from small sample households in these segments.

As a result of GPS estimations, the optimal mean household per capita expenditure was achieved between 11 and 12 years of membership duration. The corresponding optimum values of yearly average household per capita consumption expenditures at these optimum years of membership duration are at a dose-response of Birr 4263.75. The concern here is where the desired optimum membership duration should be maintained. Forest management implies reduced transaction prices for its participants and improves the coherence of forestry movements at the product scale. Increasing the scale of the control unit improves market positioning, allows more technical management, and improves the corresponding household per capita consumption expenditures.

Sensitivity Analysis

Recently, checking the sensitivity of the estimated results has become an increasingly important topic in the applied valuation literature **(Caliendo & Kopeining, 2008)**. The matching method is based on the conditional independence or unconfoundedness assumption, which states that the evaluator should observe all variables simultaneously influencing the participation decision and the outcome variables. The main drawback of GPS as an impact analytical technique is that its fundamental assumption is statistically non-testable, i.e., weak unconfoundedness. They were matching via generalized propensity score, in this study, conditional on sample household membership duration density-independent of household per capita consumption expenditure. The credible explanation is to carry out various sensitivity tests on the main finding **(Kluve *et al*., 2012)**. First, indirect assessments were guided by examining the link between treatment and added livelihood indicators to predict the primary outcome variable. Different sensitivity analyses were performed to improve the reliability of identifying the sensitivity of the version used in the outcome.

The association between membership duration and household per capita expenditure is the program's cumulative effects on various household livelihood activities. Three livelihood indicators were analysed for their average dose-response: per capita household income from non-timber forest products and crop and livestock per capita household income.

Impact of membership duration on household income from non-timber forest products

Considering reasonable confidence bandwidth, results in Figure 5 reveal that household income from non-timber forest product sales strongly increases with membership length in the area. Though the causal relationship is positive, revenue from non-timber forest products sales strongly responds to the membership duration dose in the study area. Results are also revealed in the marginal effect figure (Figure 6). The livelihood activities of households in the study area consist of forest-related activities, mainly harvesting of NTFPs, and off\non-farm activities. With such diversified income sources, the exploitation of NTFPs plays an important role - Farmers harvest NTFPs from the forest for different commercial and subsistence purposes. The income derived from the sale of NTFPs demonstrates that the forest plays a vital role in household incomes. Most NTFPs (forest coffee, honey, and spices) were collected for sale and contributed 47% of annual household income.

Thus, households in the forest area use NTFPs for household consumption and as a source of cash income. Individuals who lived in the area for long years of exposure to the program and had an excellent experience using NTFPs were selected.

Impact of membership duration on household income from crop production

Annual household income from crop production has a positive causal relationship with membership beyond four years (Figure 7). However, Figure 7 shows the negative relationship between this duration dose (38% of the sample households fell). From the right-hand side of the constitution, it is observed that the maximum marginal effect is attained. membership duration of 6 - 8 years' dose

Impact of membership duration on household income from livestock production

Annual household income from livestock production has a positive causal relationship with membership beyond four years (Figure 8). The effect of the entry rate concerning the continuous years of membership duration in the program was firmly incorporated with additional income obtained from forests. Longer membership duration can survive based on their livestock; they diversify their livelihood by earning income from sources other than farming strategies **(Gebru *et al*., 2018).**

Table 7: Common support region

Treatment D	Dosage group	Min	Max
≤ 6	Duration<6 (GPS_G1)	0.0022	0.2142
	Duration>6 (GPS_G2&3)	0.0010	0.1107
	Common support Region [0.001 , 0.2142]		
6 to 9	6<Duration ≤ 9 (GPS_G2)	0.0202	0.1172
	Duration ≤ 6 & Duration >9 (GPS_G1&3)	0.0059	0.1024
	Common support Region [0.0059 , 0.1172]		
>9	Duration>9(GPS_G3)	0.0026	0.1003
	Duration ≤ 9 (GPS_G1&2)	0.0106	0.1372
	Common support Region [0.0026 , 0.1372]		

Source: Results based on survey data, 2018.

Table 8: Results of dose-response consumption expenditure

Consumption Expenditure	Coef.	Std. Err.	t-value
MDurn	-271.03	179.78	-1.53
MDurn _square	37.36***	12.01	3.11
GPS	-8656.27	6454.54	-1.34
GPS_square	41368.4*	22359.51	1.85.
MDurn *GPS	222.93	441.75	0.54
Intercept	2695.14***	676.46	3.98
Adj R-squared	0.44		
Obs.	241		

Source: Results based on survey data, 2018.

Figure 3: Common support region

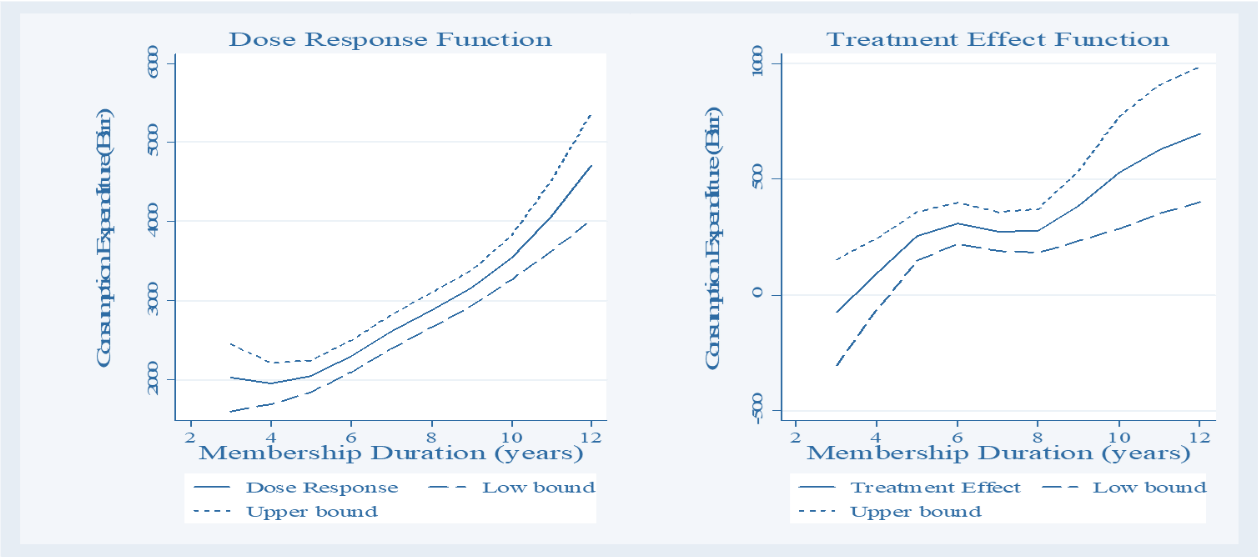

Figure 4: Average dose-response estimated for Per-Capita consumption expenditure [Quadratic] HCPCexp.

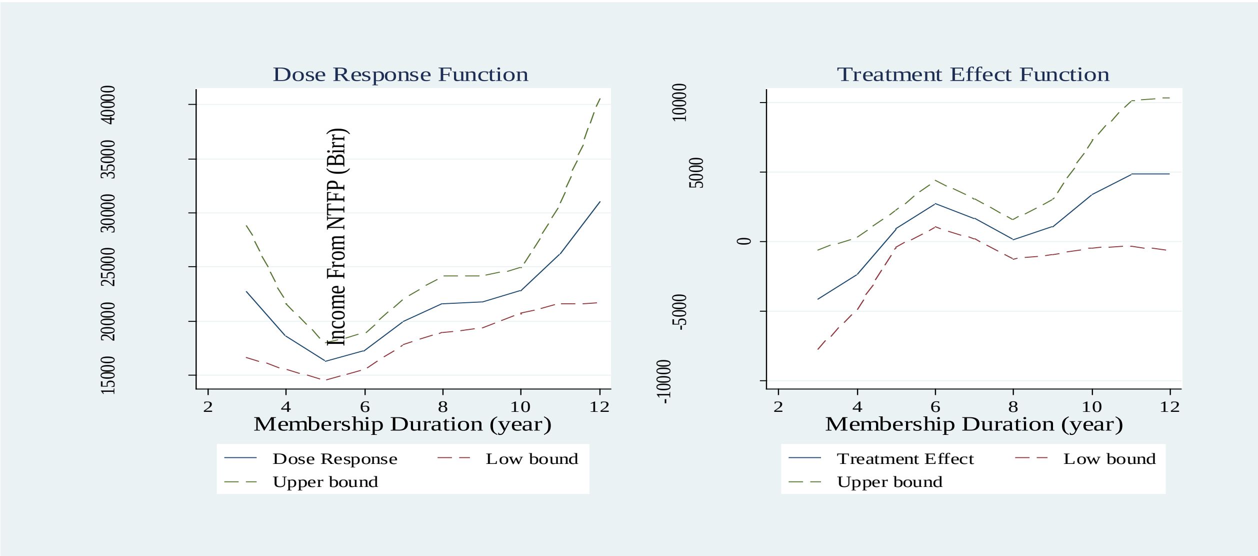

Figure 5: Average dose-response estimated for household income from non-timber forest products [Quadratic] IncmNTFP.

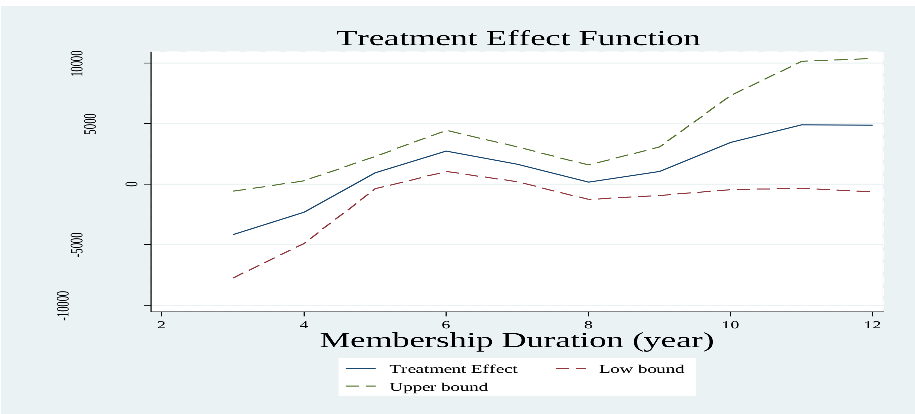

Figure 6: Marginal dose-response estimated for household income from non-timber forest products(IncmNTFP)

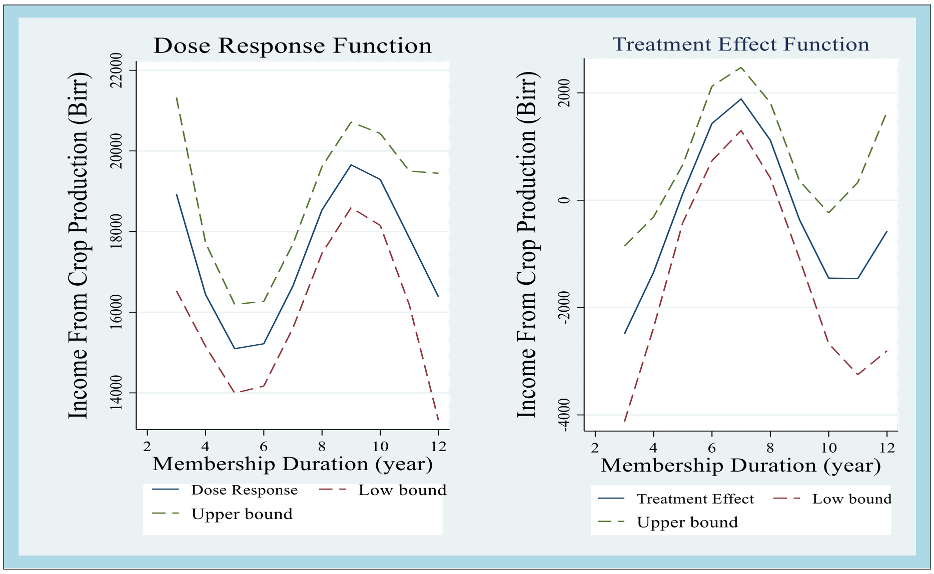

Figure 7: Average dose-response estimated for household income from crop production [Quadratic] IncmCrop.

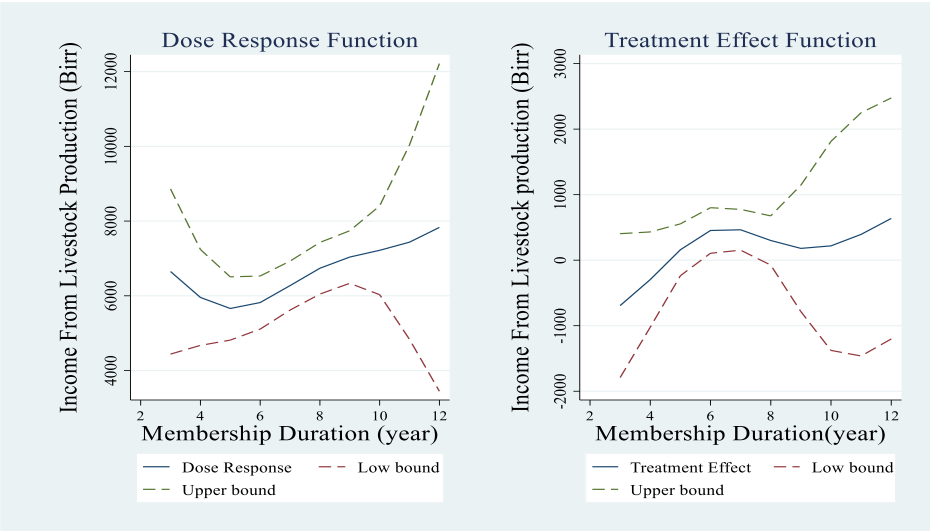

Figure 8: Average dose-response estimated for household income from livestock production [Quadratic] IncmLvstk.

DISCUSSION

In sum, in the study areas, all the three livelihood indicators have relationships with membership duration in the PFMP dose as a priori expectations. These results confirm and strengthen the impacts of membership duration on members' yearly consumption expenditure. Figures 5 and 6 show the results of estimated average dose-response function curves and marginal effects curves characterized changes in a causal treatment analysis, respectively. The shape of the dose-response curves shows increasing marginal effects. The values of results exhibit the marginal impact with a length of membership of the treatment significantly, affecting consumption expenditures. When stayed years of members in the program increase, the households have the more excellent marginal value of consumption expenditures. The slope of the dose-response curve is flatter at higher levels of treatment. Considering the plot with the first six years of membership increases at an increasing rate and reaches the maximum, indicating the association. This association of causal inference specification for respective outcome variables shows households in the forest area use NTFPs for household consumption and as a source of cash income. Individuals who lived in the area for long years of exposure to the program and had an excellent experience using NTFPs were benefited. Similar to this study, **Rai *et al.*, 2016** emphasize that household involvement may have made them more viable and produced more profits because older forest user groups provide more gains to households than more recently established ones.

Figures 4 and Figure 8 show the separate dose-response curves for per-capita consumption expenditure and household income from livestock production. There is a significant distinction between the three groups, at a 5% significance level. The dose-response curves have similar intercepts and shapes; both plots are steeper, around six years of membership duration. However, the impact marginally significant at a 5% significance is similar across their duration from 6 - 8 years in terms of the outcome measurement it's different. One year or concise duration does not appear to drive the main result in Figure 4. was observed. Increasing throughout the graph leads to improvements in households' livelihoods, i.e., the higher the membership duration affects consumption expenditure beyond nine years of membership duration. The shapes of the plots are pretty similar to the results from the main model specification. Thus, results from specifications indicate membership duration to PFMP affects annual per-capita household consumption expenditure of rural households, the period increases.

Further, the slope gradually increases, eventually flattening out around just over nine years' treatment duration, suggesting that beyond nine years' treatment duration, result in additional income (Figure 5). This result supports the findings of **Gelo & Koch (2014)** and ***Ameha et al.* (2014b).** In the determined association in PFMP membership groups, strengthening south-western membership groups increased revenue and raised forest income from timber products.

Generally, this result from the generalized propensity score and dose-response functions revealed that a positive effect of membership duration to the program brings about better benefits in terms of per-capita consumption expenditure.

Surprisingly, the plot showed in Figure 7 dose-response relations between length of membership and income from crop production was found to be between more extended and the medium length of membership in the program. The strong association could offer a compelling challenge to the future implication of the program management. This observation aims to determine the impact duration of the participant's membership on participatory woodland communities and intake expenditures. The effect membership years of the period of members has not been analysed through everyday benefits received from the program. Take a look at implying long-term effects on members of participatory forest management

CONCLUSIONS

In this study it has been observed from descriptive analysis based on households intensity of duration longer length membership households and distance to the nearest market is a positive relationship, in contrast shorter duration members household is travel long distance to PFMP forest point in particular ratio analysis F-test results are statistically significant differences among the three groups of membership duration the result showed a substantial difference in the family size of the farmers livestock assets NTFPs income crop production and livestock production are statistically significant among the three groups at less than five percent probability level moreover the result of this study has shown that as the size of livestock is increased the gross margin earning status of the participant farmers will increase here the stakeholders should critically evaluate the real benefits that the members can get from the livestock the correlation test also revealed that the variables provision of membership duration density in different specification models showed substantial positive effects on household per capita consumption expenditure farm income shows positive and significant results in determining the consumption expenditures status of households the correlation test also revealed that the variables provision of membership duration density in different specification models showed substantial positive effects on household per capita consumption expenditure farm income shows positive and significant results in determining the consumption expenditures status of households

Spline regression results between consumption expenditure and treatment duration are positive, and the explanatory power of the treatment is high. The differences among three groups at the Households level in the study area obtain their farm income from non-timber forest products selling, livestock assets, animal by-products, and crop production. Introducing a better forest management system can improve NTFPs harvesting yield, resource utilization, and available credit that helps purchase modern agricultural inputs providing adequate rural infrastructure such as large and small-scale irrigation schemes.

The result of the econometric analysis was also revealed by following extensive steps on GPS application and the mean dose-response functions, which shows inferences to secure conclusions of the association. Evaluating associations between membership duration and consumption expenditure inform that participatory forest plays an essential contribution to bear members enjoying their participation. Overall program management has generated opportunities, infrastructure development, and enhanced non-timber product marketing, collaborative planning, and action. Although the effects are concentrated on their sufficiently longer forest program participants, medium and shorter duration membership benefit flows and income are compromised

In developing countries like Ethiopia, PFMPs have a fundamental role in natural resource protection. Impact study provides empirical evidence on how the members of participation in PFMPs improve their livelihoods at the household's level. This analysis will have expected to show government regulators' policy options and improve the Management of the PFMPs in allocating resources that satisfy the two-fold outcomes, protecting the forest and enhancing the livelihoods of the beneficiaries. It also enables investors, stakeholders, policymakers, donors, and development practitioners to better understand the impact of PFMP on livelihoods and inform local communities' preferences regarding their economic priorities. Contribute to designing proper and effective forest management program strategies that support local communities' socio-economic needs compatible with conservation objectives - the natural resource sector conservation programs for monitoring the status and influencing their rural participation performance. Developing countries have recently adopted community members' involvement in forest membership structures, such as forest users' cooperatives (FUCs) and forest Users group (FUGs). While this type of program has been observed in the study areas of PFMP to raise smallholder incomes, there is evidence on saving and consumption expenditure responses to such income gains from the program.

This study examines the relationship between annual per-capita consumption expenditure and the duration of treatment (household membership duration) in rural households in south-western Ethiopia. The analysis revealed that the PFM program had raised membership households' annual yearly consumption expenditure. The average program impact at the optimum level of membership duration dose around at ETB 4263.75 in treatment dose-response of per-capita consumption expenditures in each membership duration separately. Further, the results of membership duration analysis at the household level indicate that PFMP in south-western Ethiopia is economically influential in the present socio-economic context. The results also reveal that the impact of PFMP increases with the length of membership duration. It implies that members of longer membership duration have higher returns on their contribution than those of shorter membership duration households. There could be two explanations for these findings. Firstly, longer membership duration households' practices yield technologies management, improving forest conditions relative to recently entered member's families **(Pokharel, 2012)**. Secondly, longer membership duration households harvest large quantities of harvestable non-timber forest products, and the amount of harvested non-timber forest products is directly linked with the household benefits. In general, the effect of the entry rate concerning the continuous years of membership duration in the program was firmly incorporated with additional income obtained from forests.

Membership duration to forest management has detrimental effects on adopting new, improved markets integration in their NTFPs and enhanced quality of products. In addition, membership duration to the programs was observed to lead to higher yields for bananas and related products. The association for strengthening membership duration of participation in the PFMP should also concern policymakers, especially considering that the country invests in agricultural extension through groups. Therefore, it is recommended that strict follow-up work be done on the members of the participating forest communities to encourage new incomes and integrate the socio-economic network more closely with the forest ecosystem and biodiversity.

Although the relationship between forest participating communities' longevity and income is substantial, the program has been focused on the more extended duration of the forest program. Accordingly, it is proposed to mitigate the effects on management functions, and future research lines should be presented based on the limitations of the work and the dynamic nature of the participation.

Recommendation

Therefore, it is recommended that more work be done on the participating household members by encouraging new forest-related income sources and integrating the socio-economic network more closely with the forest's ecosystem services. Although the relationship among participating members of households' longevity and income is substantial, the program has been focused on the medium and longer duration of the forest program participating. Accordingly, it is proposed to mitigate the effects on the association of annual household income functions, and membership duration should be strict follow-up on their performance by the concerned entity presented based on the limitations of the program and the dynamic nature of the participation.

Based on this fact, the aspects are suggested for cognizance in optimizing the productivity in the participatory activities in study districts when broadly viewed as enhancing the benefits gained from PFMP operations are limited in volume due to farmers in the study area having limited access to modern agricultural inputs fertilizer and a comprehensive yielding variety institutional support credit and extension advice thus this study highlighted critical recognition and PFMP activities policy consideration has given in the area of research influence farmers marketing of farm produces changing cultures of farmers towards for members

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FARM SIZE AND EFFICIENCY NEXUS: EVIDENCE FROM A META-REGRESSION

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ABSTRACT

Research background: Many studies have reported the relationship between farm size and productivity. Whilst some meta-regressions on efficiency have been published, none has addressed the issue of farm size efficiency relative to the dimensions of productive efficiency and its variants.
Purpose of the article: We investigated the effect of farm size on productivity in Ghanaian agriculture within a meta-regression framework.
Methods: Using data on 93 primary studies with 177 observations on efficiency in agriculture in Ghana, the Ordinary Least Squares estimator was applied in estimating the meta-regression model, a form of meta-analysis that specially formulated to assess empirical economics research. The farm size–efficiency effects were computed based on the Wald.
Findings, value added & novelty: The results were mixed. Whilst no farm size-efficiency nexus was established for allocative and scale efficiencies, the inverse effect was confirmed in the case of the cost-economic, profit, technical and metafrontier technical efficiencies. Improved technology would be compatible with reduced farm size, reduction of the technology gap that would move farmers closer to the metafrontier. We contribute to the farm size-efficiency debate as we performed a quantitative review of the farm size-efficiency relationship. We addressed the farm size-efficiency relationship within the meta-regression framework and accounted for the full range of efficiency measures. Unlike other meta-regressions that used the standard error of the estimates, we obtained additional effect size, that for farm size-efficiency, our key result, from the specified model. We then dissociated the effect size into the range of efficiency measures reported in the primary studies. The paper covers data on farming in Ghana.

Keywords: meta-regression; metafrontier technical efficiency; scale efficiency
JEL Codes: D13; Q12; O55

INTRODUCTION

Land is important to agricultural production. As the soil, it is a store of nutrients and provides mechanical support to crops and pasture. As a ground surface, it serves as space for farm structures, grazing animals, ponds, and water bodies for holding irrigation water and a home for aquatic life, among others. Total agricultural land globally for 2017 is estimated at 4,827 mega hectares (m ha), with Africa contributing 1,139.5 m ha (and Ghana 15.7 m ha) (**FAOSTAT, 2020**). Together with other resources like labour and capital, the area of land, measured in System International (SI) units as hectares, is essential in determining the population of plants, the number of products to be obtained and total biomass (**Englund, 2020; Gopal *et al*., 2020; Perpiña *et al*., 2013; Prokop, 2018**).

How effectively land and other resources contribute to output is referred to as productivity. Narrowly, input productivity is the ratio of the agricultural output to a unit of the input, thus, the productivity of land (also designated as yield), labour productivity and productivity of capital (**Boyes & Melvin, 2012; Cowell, 2018**). As there are varied capital resources including fertiliser, other agrochemicals and farm machinery, the productivity is expressed in terms of the specific capital input. A broader measure of productivity is productive efficiency. Technical efficiency is the extent to which the potential output is obtained (**Farrell, 1957**). Other counterparts of technical efficiency include allocative, cost, economic, profit, and scale efficiencies (**Fried *et al*., 2008; Lovell & Schmidt, 1988; Simar & Wilson, 2020**). As profit is revenue less cost, revenue efficiency is also known in the literature (**Hansen *et al*., 2019; Soleimani-Chamkhorami *et al*., 2019; Mostafaee & Hladik, 2019**).

Sen (1962, 1966) pioneered research into farm size and land productivity relationships. Following the finding of an opposite relationship, many studies have investigated the issue further (**Bardhan, 1973; Byiringiro & Reardon, 1996; Carletto, Savastano & Zezza, 2013; Fan & Chan-Kang, 2005; Feder, 1985; Julien, Bravo-Ureta & Rada, 2021; Li *et al*., 2013; Mazumdar, 1965; Van Asdul, 2020**). Notwithstanding the inverse relationship, **Alvarez & Arias (2004), Freitas *et al*. (2019)** and **Singh *et al*. (2017)** concluded that the relationship between the two is positive. **Adachi *et al*.**

(2010), Bojnec & Latruffe (2007), Li *et al.* (2013), Rahman *et al*. (2012) and **Sarpong (2002)** however found no significant relationship between farm size and land productivity. Considering the conflicting findings, what is the relationship between farm size and productivity based on combined evidence? We conducted a meta-regression of farm size and efficiency, broadly defined, to respond to the question.

Studies on farm size-productivity relationship abound. However, review papers on the subject are rare. **Saini (1980)** reviewed the association between farm size and income per acre for India. **Shi and Lang (2013)** addressed the subject in a review of studies on China with a focus on other measures of productivity. Several meta-regressions on technical efficiency and productivity in agriculture have also been published (**Djokoto, 2015; Djokoto *et al*. 2016; Djokoto & Gidiglo, 2016; Geffersa *et al*., 2019; Hina & Bushra, 2016; Mareth *et al*., 2016; Solomon & Mamo, 2016)**. However, none of these addressed the farm size-productivity nexus. Whilst review studies on farm size-productivity relationship are few, quantitative reviews are non-existent. Our paper makes the following contributions to the literature. First, we perform a quantitative review of the farm size-efficiency relationship. Second, unlike other meta-regressions that used the standard error of the estimates or its equivalent and their transformations, so that the estimated coefficients become the effect size, we obtained additional effect size, that for farm size-efficiency, our key result, from the specified model. Thirdly, we dissociated the effect size into the range of efficiency measures reported in the primary studies.

On a debated issue such as the farm size-productivity relationship, for which the literature is full of many and conflicting findings, analysing these jointly offers one of the most reliable approaches for a definitive contribution to the issue. Thus, we applied a meta-regression analysis.

Many primary publications that studied the effect of farm area on agricultural output focused on partial (narrow) measures of productivity; output per unit area **(Carter, 1984; Barrett, 1996; Ansoms, Verdoodt & Van Raust, 2008; Dieninger *et al*., 2018; Cheng, Zheng & Henneberry, 2019; IPBES, 2018; Van Ausdal, 2020)**. However, since the partial productivity measures may favour small producers, a broader measure of productivity measures would be preferable **(Anang *et al*., 2016; Kumbhakar & Lovell, 2000; Li *et al*., 2013)**. Not only do we use primary studies that measure productivity broadly, but we also estimate the farm size-efficiency relationship for a range of the broad efficiency measures reported in the primary studies. These contributions are based on data on Ghanaian agriculture.

The next section presents a review of the literature on farm size efficiency relationships. The data and methods section follows. Before the conclusions and conclusions section, the results are presented and discussed.

LITERATURE REVIEW

The literature context regarding the subject consists of the foundations of the farm size – efficiency relationship, the empirical review, and the methodological context of meta-regression.

Some foundations of the opposite farm size and productivity association

The inverse relationship has been explained variously. **Sen (1962)** acknowledging the general inverse relationship between farm size and productivity provided two reasons, the indivisibility of inputs e.g., bullocks and that family labour is large in total labour, so that as farm sizes get smaller, total labour per acre increases.

Chayanov (1966) put forward the theory of self-exploitation. The thesis states: "the degree of self-exploitation is determined by a peculiar equilibrium between family demand satisfaction and the drudgery of labour itself" (p. 4). Stated differently, the productivity of labour is mainly explained by the constitution of the family and its size, the number of work-capable members, the productivity of the labour unit, and the extent of labour deployment **(Nepomuceno, 2019)**. This is termed the degree of self-exploitation. Thus, a working family rich in labour without hiring opportunities, but constrained in the land, has no option but to apply this labour to the land. Whilst this would increase the output per unit of land, labour productivity may decrease.

Others have adduced imperfect input factor markets which results in the land, labour force and credit market differences between the large-scale farmers and small-scale farmers (**Sen, 1966; Carter, 1984; Lamb, 2003; Li *et al*., 2013; Newell *et al*., 1997; Reardon *et al*., 1996)**. According to **Sen (1966, p. 443)** "The peasant family is guided properly by its calculation of the real labour cost, reflecting the rate at which the members are ready to substitute labour for output, but the capitalist farmer is misguided by an inefficient market mechanism. His allocation is, therefore, correspondingly distorted".

Differences in quality of land, measured by soil type, irrigation, and the value of farmland and utilisation degree also account for the opposite relationship between farm size and productivity **(Byiringiro & Reardon, 1996; Lamb, 2003). Assuncao & Ghatak (2003)** explained that heterogeneities in farmers' farming skills and occupational choice and resources account for the inverse relation. In the view of **Eswaran & Kotwal (1985)** and **Li *et al*. (2013),** transaction costs, supervision costs differences and principal-agent problems in the farm organisation could accentuate the opposite relationship.

Empirical review

Reviewing several studies on farm size and efficiency in India, **Saini (1980)** acknowledged the opposite association of farm size-revenue productivity in the 1950s. The non-uniformity of income arising from non-uniform distribution of land was to some extent reduced by productivity differences between small and large farms **(Ali & Deininger, 2014)**. Since the Green Revolution, however, this relationship has undergone a significant change. As farm size increased, the income increased more than proportionately. **Saini (1980)** suggested that changes might have taken place during the seventies which might have negated the conclusions of the evidence from earlier years.

Placing the farm size-agricultural productivity association debate within the Chinese environment, the review of **Shi & Lang (2013)** acknowledged the importance and policy implications for the formulation of agricultural development strategies related to the scale of operation. In a comprehensive review of studies on the subject covering China, it was found that selecting different productivity indicators would lead to inconsistent conclusions about the relationship between farm size and productivity. Previous studies mostly interpreted the traditional inverse relationship from the perspectives of incomplete factor markets and omitted variables, among others. Few explanations had been adduced to explain other types of relationships. Consequently, **Shi & Lang (2013)** suggested that in carrying out the scale operation, local governments in China should consider the regional conditions.

Three data structures are common in econometrics: time series, cross-section, and panel data. The relative strengths and weaknesses of these data structures have implications for the outcome of relationships between variables in efficiency meta-regressions. **Greene (1993)** and **Djokoto *et al*. (2020)** noted that other data structures are likely to yield less accurate efficiency estimates than panel data models given that there are repeated observations on each unit in the case of panel data. Mean technical efficiency (MTE) from cross-sectional data sets produced lower estimates than those from panel data analysis **(Aiello and Bonanno, 2016; Djokoto *et al*., 2020; Nguyen & Coelli, 2009; Thiam *et al*., 2001). Hina & Bushra (2016)** and **Djokoto *et al*. (2020)** have found technical efficiency (TE) values to be lower for cross-sectional data sets than for time series data sets. However, the data structure was unresponsive to technical efficiency **(Djokoto & Gidiglo, 2016; Djokoto *et al*., 2020)**.

The diverse strands of estimating frontier efficiency have crystallised into two main ways: stochastic frontier analysis (SFA) and data envelopment analysis (DEA). Since some of the errors in frontier efficiency models are accounted for as inefficiency, deterministic models do bias TE estimates upwards **(Kumbhakar & Lovell, 2000).** However, recent improvements in DEA efficiency measurements are expected to reduce the upward bias **(Djokoto *et al*., 2020; Emrouznejad, Parker & Tavares, 2008; Cook & Seiford, 2009; Kao, 2014; Koronakos, 2019; Mariz Almeida & Aloise, 2018)**. Nevertheless, some studies have shown that TE estimates from DEA models are higher than those from SFA models **(Bravo-Ureta *et al*., 2007; Iliyasu *et al*., 2014),** whilst the findings of **Djokoto (2015)** and **Ogundari (2014)** were inconsistent. Other studies could not differentiate TE **(Djokoto *et al*., 2020; Fall *et al*., 2018)**.

Spatial disparities in efficiency are not uncommon in the literature. Publications that focused on southern Nigeria produced higher mean technical efficiency than others **(Ogundari & Brümmer, 2011)**. The better development in the coastal regions than others culminated in better efficiency in economic endeavours for agriculture and agribusiness in Ghana **(Djokoto *et al*., 2016; Djokoto & Gidiglo, 2016)**. Recently and in a multi-sectoral study, however, **Djokoto *et al*. (2020)** found the contrary, that, MTEs for middle and northern sections were higher than those covering Ghana (and COASTL).

Time is often used to capture technological improvement because of the positive correlation between technology and time. Consequently, it is expected that efficiency would improve overtime as well. Whilst **Ogundari & Brümmer (2011)** and **Djokoto & Gidiglo (2016)** agreed with this, **Odeck & Brathen (2012)** and **Ogundari (2014)** reported the opposite. Mean technical efficiency was not found to be responsive to time in some studies **(Djokoto *et al*., 2020; Solomon & Mamo, 2016).**

Studies on efficiency and productivity have also been seen to follow the usual order of diffusion of research results; theses-working papers-conference papers-journals. Across these outlets, variations in MTE have been found **(Djokoto *et al*., 2020).** Specifically, **Djokoto *et al.* (2016), Geffersa *et al*. (2019)** and **Ogundari (2014)** found higher TE from journals as opposed to other dissemination media **(Djokoto *et al*., 2020**). Whilst **Aiello & Bonanno (2015), Djokoto & Gidiglo (2016)** found the opposite, **Djokoto *et al*. (2020)** and **Solomon & Mamo (2016)** however, concluded on significant differentiation in efficiency based on dissemination outlet.

Meta-regression

Meta-regression as a form of meta-analysis is specially formulated to assess empirical economics research **(Campbell & Fogarty, 2006; Stanley & Jarrell, 1989; Jarrell & Stanley, 1990).** Identified as "analysis of analysis" **(Glass, 1976, pg. 3)**, MRA can also be viewed as a secondary analysis. **Binder (2016), Campbell & Fogarty (2006), Stanley (2001)** and **Sterne (2009)** outlined four goals for MRA; 1. Identify the extent to which the choice of methods, design and data affect reported results. 2. Useful in explaining the wide variation found among research outcomes and proffer reasons, that emanates from studies, why the evidence on a certain issue appears conflicting or so different. 3. Propose useful approaches for future study. 4. Propose a prediction of the outcomes such a new study would arrive at. The abundance of studies on a phenomenon does necessitate MRA **(Djokoto *et al*., 2020; Hunter & Schmidt, 1990).**

As a methodology, MRA enables the analysis of results from many individual studies to integrate the findings (**Stanley, 2001; Djokoto *et al*., 2020)**. This involves searching for individual studies, identifying the appropriate measures of interest informed by the objective of the study **(Djokoto & Gidiglo, 2016; Djokoto *et al*., 2020)**. Further, MRA helps to explore the variability in the concept under investigation and its drivers **(Djokoto *et al.*, 2020; Hess & von Cramon-Taubadel, 2008; Nelson & Kennedy, 2009)**. The concept under study is usually a summary statistic, often a regression parameter **(Stanley, 2001)**.

The summary statistic in the case of efficiency MRA, the mean efficiencies (MEs) are identified and isolated from the studies assessed and the related properties noted **(Djokoto *et al*., 2020; Stanley, 2005, 2008; Stanley & Jarrell, 1989).** The data so collected is modelled using regression analysis to explore the heterogeneity and the factors responsible for variation in the summary ME. As each study may constitute an observation or data point, more than one MEs from a primary publication are included as individual data points in the regression **(Djokoto, 2015; Djokoto *et al*., 2020; Espey, Espey & Shaw, 1997)**. Evidence from the literature point to diverse estimation procedures for efficiency MRAs; fractional regression modelling, OLS, logistic, truncated regression, transformed truncated regression and Tobit **(Djokoto & Gidiglo, 2016; Djokoto *et al*., 2020; Nandy, Singh & Singh, 2018; Ogundari & Brümmer, 2011).**

Following some initial MRAs in economics, **Stanley (2001)** presented an influential review. Since then, there has been an increase in MRA applications in economics. For example, meta-regression analysis was applied by 626 papers in economics between 1980 and 2010, with a huge jump in the 2000s **(Poot, 2012)**. The first MRA on efficiency within the agricultural economics literature was published by **Thiam *et al*. (2001)**. Other MRAs on efficiency in agriculture have been published subsequently (**Bravo-Ureta *et al*., 2007; Djokoto & Gidiglo, 2016; Djokoto *et al*., 2016; Hina & Bushra, 2016; Iliyasu *et al*., 2014; Nandy *et al*., 2018; Ogundari, 2014; Ogundari & Brümmer, 2011; Solomon & Mamo, 2016)**.

MRA synthesises very different studies **(Glass, 1976; Glass *et al*., 1981)**. Notwithstanding the benefit of pooling results of previous studies, there is a shortcoming. That is, assembling different studies into a common data set, described as the 'apples and oranges' problem. According to **Aiello & Bonanno (2016)**, this shortcoming can be ameliorated by re-specifying the issue under investigation. Secondly, appropriate identification of the 'apples' and 'oranges' and their isolation in the regression model, is another curing opportunity.

DATA AND METHODS

The data, modelling and estimation procedure constitutes the materials and methods section.

Data

The starting point for the data collection was the data from **Djokoto *et al*. (2020)**. This was updated to include additional studies in 2019, 2020 and 2021. Data collection followed the recommendations of **Stanley *et al*. (2013)**. The search which yielded 3,512 publications, ended at 17:00GMT on 31st August 2021.

To be included in the metadata, the study must relate to agriculture. Additionally, SFA or DEA and its associated procedures should be the approach to the measurement of efficiency. Further, the characteristics of the study should include the agricultural sector and the geographical coverage as well as the mean of frontier efficiency or efficiencies. Furthermore, the study should report mean farm size. The use of these criteria and removal of repeated observations culminated in 93 publications with 177 observations (data points). Other authors reviewed the data extracted by one author.

Modelling

As publication bias is an issue in meta-regression, we started our modelling by specifying the equation of the funnel plot **(Djokoto *et al*., 2020; Egger *et al*., 1997; Rose & Stanley, 2005; Stanley, 2005; Stanley & Doucouliagos, 2012)** (Eq. 1).

$$MEFF_i = \beta_1 + \beta_0 SE_i + e_i \quad (1)$$

Where:

β_1 is the overarching effect-size and β_0 is the quantitative representation of the asymmetry of the funnel plot; extent of publication bias and e_i is the error term **(Djokoto *et al*., 2020).** *MEFF* is mean efficiency. Equation 1 is heteroscedastic. As a solution, both sides of the equation were divided by SE to yield Eq. 2.

$$\frac{MEFF_i}{SE_i} = \beta_1\left(\frac{1}{SE_i}\right) + \beta_0 + \varepsilon_i \quad (2)$$

Where:

β_1 is still the overarching effect size whilst β_0 denotes the asymmetry of the funnel plot. In the absence of standard errors (SE), a proxy, inverse of the square root of the sample size, was used **(Djokoto *et al*., 2020; Ogundari, Amos & Okoruwa, 2012**) (Eq.3).

$$\frac{MEFF_i}{TR_i} = \beta_1\left(\frac{1}{TR_i}\right) + \beta_0 + \delta_i \quad (3)$$

Where:

TR is the transformation variable.

The assumption for Eq. 3 is $\beta_0 \neq 0$ implies publication bias, also, $\beta_1 \neq 0$ captures a quantitative effect of the *MEFF* estimates. Where there is no publication bias, the reported *MEFF* should spread indeterminately encircling the true MEFF estimate, while the presence of a true quantitative effect supposes that the estimated β_1 has been adjusted for bias over the studies compiled. Our key variable is farm size, and this must be captured in Eq 3. Further, our dependent variable is made up of different frontier efficiency estimates (allocative, cost, profit, scale and technical). To isolate the effect of the farm size-efficiency nexus for each dimension of the frontier efficiency, we interact farm size with each of the efficiency dimensions as in Eq. 4.

$$\begin{aligned} MEFF\_TR_i &= \beta_0 + \beta_1 INV\_TR_i + \beta_2 FS_i + \beta_3 FSAE_i + \\ &\beta_4 FSCEE_i + \beta_5 FSPE_i + \beta_6 FSSE_i + \beta_7 FSMFTE_i + \\ &\beta_8 XSECTION_i + \beta_9 SFA_i + \beta_{10} DEA_i + \beta_{11} NORTH_i + \\ &\beta_{12} MID_i + \beta_{13} COSTL_i + \beta_{14} TIME_i + \beta_{15} JOURNAL_i + \\ &\beta_{16} CONF_i + \beta_{17} WP_i + \epsilon_i \end{aligned} \quad (4)$$

Whilst the inclusion helps to identify the extent to which the choice of methods, design and data affect reported results **(Campbell & Fogarty, 2006; Djokoto *et al*., 2020; Stanley 2001),** these controls also ensure minimisation and possible elimination of publication bias **(Appiah-Adu & Djokoto, 2015; Djokoto *et al*., 2020)**. The variables in Eq. 4 and their descriptions are contained in Table 1. It must be noted that the primary studies used cost efficiency (CE) and economic efficiency (EE) interchangeably, hence the construction of CEE from CE and EE.

Farm size-efficiency nexus

We use interaction terms to isolate the effect of the different frontier efficiency measures. The use of interaction terms has found use in primary efficiency studies in recent times **(Alter & Elekdag, 2020; Duval, Hong & Timmer, 2020; Hanousek, Shamshur & Tesl, 2019; Neves, Gouveia & Proenca, 2020).** These are useful in isolating economic effects **(Rajan & Zingales, 1998)**. From Eq. 4 and recalling that the dimensions of frontier efficiency on the RHS of the equation are dummy variables, β_i where i = 3, …7 are partial effects whilst β_2 is the main effect. The farm size-efficiency effect for allocative efficiency then is $\beta_2 + \beta_3 * \overline{AE}$. That for cost-economic efficiency is $\beta_2 + \beta_4 * \overline{CEE}$ whilst $\beta_2 + \beta_5 * \overline{PE}$ captures effect for profit efficiency. For scale efficiency: $\beta_2 + \beta_6 * \overline{SE}$ and metafrontier technical efficiency is $\beta_2 + \beta_7 * \overline{MFTE}$. The outstanding effect is technical efficiency, which is β_2. β_1 is the joint effect of all the efficiency dimensions. Although the efficiencies measure different aspects of the production activity, their common measure ranging between 0 and 1 make the joint-effect meaningful.

Estimation procedure

Different approaches have been used in meta-regression; fractional regression **(Djokoto & Gidiglo, 2016; Djokoto *et al*., 2020; Ogundari & Brümmer, 2011)**, Ordinary Least Squares (OLS) **(Nguyen & Coelli, 2009; Papadimitriou, 2013)** and Tobit **(Bravo-Ureta *et al*., 2007; Thiam *et al*., 2001)**. However, the transformation moved the MEFF_TR outside the unit interval. Hence, amenable to estimation with OLS.

RESULTS AND DISCUSSION

For ease of appreciation, the section is sub-sectioned into four. The background to the data, the results, discussion of the results of the control variables and finally the discussion of the farm size efficiency nexus.

Background of data

The mean efficiency ranged from 0.0740 to 0.9810 (Table 2). However, after transformation, this changed to 0.7020 to 46.2894 with a mean of 10.0187. That for the *INV_TR* ranged from 2.6458 to 88.1703. Allocative efficiency, cost-economic efficiency, and profit efficiency each contributed about 4% to the sample. This is because whilst some studies reported these jointly, others reported separate efficiencies. Consequently, these have a common contribution of observations to the metadata. Technical efficiency was most popular with efficiency investigators, hence the 76% contribution to the metadata. The mean farm size is 2.92ha. This is less than the standard deviation of 7.78 such that the variance would still exceed the mean. Hence, farm size is over-dispersed around the mean. Despite the interaction with farm size, the mean of all the efficiencies was less than 1 except *FSTE*.

More than 90% of the metadata was generated from cross-sectional studies with 78% of the 177 observations arising from SFA studies. Studies that focused on the *NORTH* constituted 54% of the metadata. Peer-reviewed journals were popular with authors of studies found, 81% of the dataset.

Table 1: Definition of variables

Variable	Definition
MEFF_TR	Mean efficiency weighted by the inverse square root of sample size (Dependent variable)
INV_TR	1 divided by the inverse of the square root of sample size
FS	Farm size in hectares
FSAE	FS interacted with allocative efficiency defined as 1 and 0 otherwise.
FSCEE	FS interacted with cost and economic efficiency defined as 1 and 0 otherwise
FSPE	FS interacted with profit efficiency defined as 1 and 0 otherwise
FSSE	FS interacted with scale efficiency defined as 1 and 0 otherwise
FSTE	FS interacted with technical efficiency defined as 1 and 0 otherwise
XSECTION	Cross-section data is 1, and 0 otherwise. Reference is panel data
SFA	Stochastic frontier analysis is 1, and 0 otherwise. Reference is distance function
DEA	Data envelopment analysis is 1, and 0 otherwise. Reference is distance function
NORTH	Studies covering Northern, Upper East and Upper West Regions. Reference: country coverage studies.
MID	Studies covering Ashanti, Brong-Ahafo and Eastern Regions. Reference: country coverage studies.
COSTL	Studies covering Central, Greater Accra, Volta, and Western Regions. Reference: country coverage studies.
TIME	Four-digit year
JOURNAL	Study published in journal as 1 and 0 otherwise. Reference is Thesis
CONF	Study published as conference paper is 1 and 0 otherwise. Reference is Thesis
WP	Study published as working paper is 1 and 0 otherwise. Reference is Thesis

Table 2: Summary statistics

Variable	Mean	Standard deviation	Minimum	Maximum
MEFF	0.6584	0.1795	0.0740	0.9810
MEFF_TR	10.0187	5.6210	0.7020	46.2894
INV_TR	15.3937	9.2371	2.6458	88.1703
FS	2.9215	7.7774	0.1500	101.5000
FSAE	0.1054	0.6578	0	5.4300
FSCEE	0.1071	0.6567	0	5.4100
FSPE	0.1624	0.9618	0	8.8000
FSSE	0.1134	0.5165	0	3.4000
FSTE	2.0873	7.6649	0	101.5000
FSMFTE	0.3450	1.9240	0	15.6000
XSECTION	0.9266	0.2616	0	1
PANEL	0.0734	0.2616	0	1
SFA	0.7797	0.4157	0	1
DEA	0.2034	0.4037	0	1
NORTH	0.5424	0.4996	0	1
MID	0.1695	0.3762	0	1
COSTL	0.0960	0.2955	0	1
TIME	2016.277	3.3434	2000	2021
JOURNAL	0.8136	0.3906	0	1
CONF	0.0508	0.2203	0	1
WP	0.0452	0.2083	0	1

Results

Although the transformation of Eq. (2) – Eq. (4) was partly to account for heteroscedasticity, this applied to the β_1 (Table 2). Model 1 (Table 3) arose from the OLS estimation of Eq. (3). The farm size efficiency interaction terms were then introduced to generate model 2. Estimation of Eq. (4) is model 3. The Breusch-Pagan test however showed that the estimation of Eq. (2) was heteroscedastic, hence the correction with robust standard errors. Likewise, models 2 and 3 were also treated similarly. Testing of each estimation showed the presence of misspecification. The inclusion of the square of the prediction of the dependent variable as additional explanatory variables are reported in Table 3 (model 1 - model 3).

The statistical significance suggests the misspecification has indeed been accounted for. The variance inflation factor for the key variables is within limits. In the case of model 3, the VIF for the SFA exceeds 10. Whilst this is below the liberal threshold of 20 (**Greene, 2019; O'brien, 2007**), the closeness to 10, alleys fear of substantial influence on the estimates of β_9. In all cases, the adjusted R squared is greater than 79%. Whilst these suggest that a substantial portion of the variability in the dependent variable is explained by the explanatory variables, the statistically significant F statistics imply that the explanatory variables jointly explain the dependent variable. The similarity of the estimates of *INV_TR* suggests the robustness of the estimates. Additionally, the estimate of the coefficient of *INV_TR* is statistically significant, and magnitude is within the unit interval. Also, the statistical insignificance of the constant across all the models implies that publication bias is absent in the meta-regression. These two observations show the necessary conditions of an appropriate meta-regression in efficiency have been met. It is commonplace to find publication bias in model 1 that would require the inclusion of control variables to eliminate it **(Aiello & Bonanno, 2016; Appiah- Adu & Djokoto, 2015; Djokoto *et al*., 2020)**. The absence of publication bias in model 1 is rather rare. This may be attributable to the correction for misspecification. Since model 3 is the full model, we focus our attention on it for discussion.

Discussion: control variables

The coefficient of the XSECTION is positive and statistically significant implying that efficiency values of cross-sectional data are higher than those from panel data (Table 3). The result is contrary to some empirical findings that reported the reverse **(Aiello & Bonanno, 2016; Djokoto *et al*., 2020; Nguyen & Coelli, 2009; Thiam *et al*., 2001)**. **Djokoto & Gidiglo (2016)** and **Djokoto *et al*. (2020)** found no effect of data structure on mean technical efficiency.

The negative and statistically significant coefficient of SFA suggests SFA efficiency estimates are lower than those from distance functions. Similarly, DEA estimates of efficiency are also lower than those from distance functions. **Djokoto & Gidiglo (2016)** however, provided contrary evidence for agribusiness in Ghana. The pertinent literature had noted DEA efficiency estimates are biased upwards (**Kumbhakar & Lovell, 2000**), although recent improvements in DEA estimation procedures have reduced the gap (**Djokoto *et al*., 2020; Emrouznejad, Parker & Tavares, 2008; Cook & Seiford, 2009; Kao, 2014; Koronakos, 2019; Mariz Almeida & Aloise, 2018**). Our result is different from others that could not differentiate efficiency estimation procedures (**Djokoto *et al*., 2020; Fall *et al*., 2018**).

The coefficients for all the spatial variables are statistically significant. Specifically, studies in the south posted higher efficiency estimates than those in the middle regions as well as those in the northern regions.

Specifically, studies covering southern regions show higher efficiency than others. The better development in the coastal regions than others culminated in better efficiency in economic endeavours for agriculture and agribusiness in Ghana (**Djokoto *et al*., 2016; Djokoto & Gidiglo, 201**6). Also, soil and agroecological conditions have accounted for this. Our finding agrees with the literature **(Ogundari & Brümmer, 2011)** for Nigeria and **(Djokoto *et al*., 2016; Djokoto & Gidiglo, 2016; Djokoto *et al*., 2020)** for Ghana. Our findings are contrary to the recent conclusion of **Djokoto *et al*. (2020)** for multiple sectors of Ghana. That is, MTEs for middle and northern sections were higher than those covering Ghana (and COASTL).

The coefficient of TIME of 0.0839 is statistically insignificant signifying that collectively, the efficiencies did not change over time. Although the sign of the coefficient seems to agree with the existing literature on efficiency progression **(Aiello & Bonanno, 2016; Ogundari & Brümmer, 2011)**, the finding certainly disagrees with efficiency regression **(Iliyasu *et al*., 2014; Ogundari, 2014)**. Other agricultural efficiency meta-regressions certainly agree with our finding **(Brons *et al*., 2005; Nandy *et al*., 2018; Solomon & Mamo, 2016; Thiam *et al*., 2001)**.

The coefficients of the study dissemination media are statistically insignificant. This result is like the findings of **Djokoto (2015), Djokoto *et al*. (2020)** and **Solomon & Mamo (2016)** but departs from others. The result implies the mean efficiencies did not vary across these media.

Discussion: Farm size-efficiency nexus

Although the frontier efficiencies measure different aspects of efficiency, values close to 1.00 imply better efficiency compared to values close to 0.00. Therefore, the overall efficiency effect size of 0.69 shows the agriculture decision-making units in the primary studies attained about 70% of their potential, equal to the 0.70 found by **Djokoto *et al.* (2020)** for all industries in Ghana (Table 3). The inefficiency (gap) of about 30% can be closed without the use of additional resources.

The Wald of the farm size – efficiency effect is reported in Table 4. The sign for all six is negative. Thus, the farm size-efficiency nexus may be negative. This fits into the early works of **Saini (1980)** in India. The congruence may be attributable to the similarities of farm structures. Also, the non-uniformity of income arising from non-uniform distribution of land was to some extent reduced by productivity differences between small and large farms (**Ali & Deininger, 2014**). **Julien *et al*. (2021)** also recently showed the inverse nexus suggesting that the distribution of farm size and TE is quadratic.

The chi-square test of the magnitudes of the Wald shows statistically insignificant Wald for allocative and scale efficiencies effects. These mean notwithstanding the negative sign, the effect of farm size on allocative and scale efficiency is neutral. Indeed, there is no discernible effect. The Wald of the other four (cost-economic, profit, technical and metafrontier technical efficiency) are statistically significant. Thus, a negative farm size – efficiency nexus for cost-economic, profit, technical and metafrontier technical efficiencies exists.

The reference frontier for efficiency measurements in the model is the metafrontier, an overarching frontier that envelopes the group frontiers. Thus, by construction, MFTE is lower than TE. Nonetheless, the MFTE essentially measures technical efficiency, the extent to which the observed output is close to the potential or frontier output. The farm size-metafrontier effect size of -0.0493 implies that an increase in farm size by 1 hectare would induce a 0.05 reduction in MFTE. This is an inverse relation, which is not surprising. Also, the effect for technical efficiency is -0.0194. This is lower than that of TE. The reason is that since the metafrontier is farther from the observed output than the TE frontier, larger adjustments would be required for the MFTE than for the TE in response to farm size.

It must be recalled that within the production function framework, the observed output result from the physical relationship or combination of the classical factors of production, land, labour, and capital. Capital such as pesticides and machinery (e.g. tractors) can easily be substituted for labour. However, this is more beneficial and cost-effective with large farm size. Farm holdings of 90% of farmers do not exceed 2 hectares **(MOFA, 2007**). Fertiliser usage is 7.4 – 13.4 kg/ha (**MOFA, 2009**; **Benin *et al*., 2013**). This is behind the average for other developing regions of the world such as South Asia (104 kg/ha), Southeast Asia (142 kg/ha) and Latin America (86 kg/ha) **(Benin *et al*. 2013; Crawford *et al*. 2006).** The usage of other agrochemicals such as pesticides and herbicides in Ghana for 2008-2017 averaged 376 tonnes/year compared to 1894 tonnes/year for Africa **(FAOSTAT, 2020).** Tractor per 100sq. km of arable land has declined from 8.183 in 1985 to 4.518 in 2005 **(World Bank, 2020).** These levels of input use are associated with small farm sizes. However, the nature of the technology (the combination of inputs) is such as to produce an appreciable level of efficiency. The arguments of indivisibility of inputs e.g., bullocks; than family, labour looms large in total labour so that as farm sizes get smaller, total labour per acre increases; imperfect input factor markets which result in differences of land, labour force and credit market between the large- and small-scale farmers (**Carter, 1984; Li *et al*., 2013; Newell *et al*., 1997; Reardon *et al*., 1996; Sen, 1962, 1966)** can explain our results.

The gaps in the input use noted earlier, suggest a technology that is incompatible with large farm size. On the other hand, a technology change would be necessary for reduced farm size **(Li *et al*., 2013).** The adoption of modern agricultural technology including breeding of input-intensive seeds and chemical fertiliser usage would improve land productivity **(Li *et al*., 2013),** without the need for an increase in land size, thus being scale-neutral **(Hayami & Rutan, 1985; Li *et al.*, 2013).** However, the use and spread of agricultural technology have a positive association with land size **(Feder, 1980; Just & Zilberman, 1983; Hu *et al*., 2019; Li *et al*., 2013; Rodewald Jr & Folwell, 1977).** Thus, technology change would increase observed output, reduce the technology gap, and move farmers closer to the metafrontier.

To be cost and economically efficient, farm size must decline. This is because the reduction in farm size would help the producer minimise costs given the input prices. As cost influences profits given the revenue, it is unsurprising that the Wald are similar. As the dimensions of efficiency are largely managerial, the managerial reasons in the literature are apt. There are heterogeneities in efficiency in Ghanaian agriculture (**Djokoto & Gidiglo, 2016; Djokoto *et al.*, 2016**). These arose from heterogeneities in farmers' farming skills and occupational choice as well as resources (**Assuncao & Ghatak, 2003).** Also, differences in transaction costs, supervision costs as well as principal-agent problems in the farm organisation exist (**Eswaran & Kotwal, 1985; Li *et al.*, 2013).** These reasons account for the inverse farm size-efficiency nexus.

Table 3: Estimation results

	1	2	3
VARIABLES	*MEFF_TR*	*MEFF_TR*	*MEFF_TR*
INV_TR	0.7164***	0.6797***	0.6895***
	(0.0685)	(0.0676)	(0.0559)
FS		-0.0138***	-0.0194**
		(0.0052)	(0.0079)
FSAE		0.2723	0.3064
		(0.2360)	(0.1918)
FSCEE		-0.0675	-0.0408
		(0.1847)	(0.1383)
FSPE		-0.1150	-0.2500**
		(0.1657)	(0.1148)
FSSE		0.6643***	0.1852
		(0.2093)	(0.3013)
FSMFTE		-0.4119***	-0.4819***
		(0.0506)	(0.0702)
XSECTION			1.1361**
			(0.5033)
SFA			-3.6392***
			(1.2034)
DEA			-5.4403***
			(1.2548)
NORTH			1.5010***
			(0.4792)
MID			3.0711***
			(0.5248)
COSTL			2.5372***
			(0.6016)
TIME			0.0839
			(0.0914)
JOURNAL			0.6677
			(0.6363)
CONF			-0.1111
			(1.1910)
WP			-1.2490
			(1.2180)
PMEFF_1_SQ	-0.0075***		
	(0.0024)		
PMEFF_2_SQ		-0.0064***	
		(0.0024)	
PMEFF_3_SQ			-0.0058***
			(0.0019)
CONSTANT	-0.0709	0.4664	-167.9933
	(0.7095)	(0.6834)	(184.0563)
Model diagnostics			
Observations	177	177	177
VIF	8.58 (*INV_TR*)	8.99 (*INV_TR*)	11.09 (*SFA*)
Adjusted R sq.	0.7934	0.8034	0.8101
F statistic	637***	265***	244***

Note: Robust standard errors in parenthesis. Significance levels: * p<0.10, ** p<0.05, ***p<0.01

Table 4: Farm size – efficiency effect

Efficiency dimension	Wald	Chi square statistic	Effect
Allocative	-0.0073	0.43	Neutral
Cost/economic	-0.0210	4.85**	Negative
Profit	-0.0293	12.20***	Negative
Scale	-0.0089	0.24	Neutral
Technical	-0.0194	6.11**	Negative
Metafrontier technical	-0.0493	26.08***	Negative

Note: Significance levels: ** $p<0.05$, *** $p<0.01$

CONCLUSIONS AND RECOMMENDATIONS

We contribute to the farm size-efficiency debate by performing a quantitative review of the farm size-efficiency relationship. Unlike other farm size-efficiency studies that used factor productivity, we employed all dimensions of the comprehensive efficiency in production theory, reported in the primary studies to investigate the farm size - efficiency relationship. We used data on 177 primary studies on efficiency in agriculture of Ghana and estimated a model with interaction terms using OLS.

We found no farm size-efficiency nexus for allocative and scale efficiency. However, we found a negative effect for cost-economic, profit, technical and metafrontier technical efficiency nexus with farm size. As the negative sign implies a reduction in farm size to induce higher *CEE*, *PE*, *TE* and *MFTE* concurrently, this presents an opportunity to change technology. Thus, we recommend technology change in Ghanaian agriculture. Specifically, increased use of fertiliser and other agrochemicals, tractors, and improved management skills. As the cost of these is one of the limiting factors, financing arrangements supported by government and non-governmental organisations would be necessary.

As the existing evidence on the inverse farm size efficiency relationship has largely been based on farm size and land productivity, our conclusion of a negative farm size nexus for four dimensions of efficiency is instructive.

We used the mean efficiencies and mean farm size as key variables for Ghana. As attempts to explore the quadratic effect of the farm size productivity resulted in serious multicollinearity issues with the key variables, this could be explored for other countries and on the global stage. These could provide insight into the possible quadratic effect of farm size and a cross country perspective to the combined evidence. The meta-regression approach could also be adopted to examine the farm size efficiency nexus for large farm size studies.

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THE EFFECT OF ADOPTION OF IMPROVED VARIETIES ON RICE PRODUCTIVITY IN THE NORTHERN REGION OF GHANA

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ABSTRACT

Research background: Adoption of improved rice varieties remain paramount in fighting food and nutrition insecurity across sub-Sahara Africa (SSA). A lot has been done in the space of the adoption of agricultural innovations and food and nutrition insecurity. However, studies on the drivers of improved rice variety adoption and its effect on rice output, considering time and location-specific factors, are limited.
Purpose of the article: This study estimated and examined the drivers and effect of improved rice variety adoption on rice output in the northern region of Ghana.
Methods: A multistage sampling technique was employed to select 404 rice farm households in the northern region of Ghana. Propensity Score Matching (PSM) approach was used to analyse the data.
Findings, Value added & Novelty: This study provides literature on drivers of improved rice variety adoption and its effect on rice output, by jointly considering time and location-specific factors. The empirical results revealed that adoption of improved rice varieties has significant positive effect on rice output of farm households. This could translate into reducing food and nutrition insecurity and the importation of rice into Ghana. Similarly, improved rice varieties adoption is positively and significantly affected by family labour, membership in FBO, farmers' perception of rainfall, awareness of government rice policy, telephone ownership, and closeness to input markets. However, the adoption of improved rice varieties bears a significant negative relationship with the age of a farmer and mechanization. To enhance rice productivity and food security outcomes, the study recommends that the development of enhanced rice varieties responsive to current climatic situation. Dissemination and promotion of the varieties should be given priority among stakeholders in the rice value chain. Farmers should be encouraged to join or form farmer-based organisations (FBOs) and support their farm work with family labour to minimize rice production costs due to external payments. Access to market by farmers should be enhanced by improving rural road networks, especially in the rural areas where rice production takes place. Government policy towards rice production should be well designed and communicated to rice farmers since awareness of government rice policy stimulates improved rice varieties adoption among rice farmers.

Keywords: adoption; improved rice varieties; propensity score matching; logit; Northern Ghana
JEL Codes: R52; R58; H41

INTRODUCTION

The significance of rice for achieving food security and poverty reduction in the world has been acknowledged **(Belayneh & Tekle, 2017)**. The food crop commodity is the second to maize in the area of production and productivity in West Africa, including Ghana **(MoFA, 2016).** The adoption of green agricultural technologies in the rice sector is necessary for the transformation of food systems and economic growth **(Webb & Block, 2012; Dzanku *et al.*, 2020**). However, the adoption of green agricultural technologies in the rice sector in Ghana faces a lot of challenges, resulting in low adoption and rice output. In Northern Ghana, where the food crop contributes substantially to food systems and socio-economic transformation, the rice productivity is found to be below the national average **(Azumah, 2019; MoFA, 2020).** Among the reasons for low rice productivity is the low uptake and utilization of enhanced rice varieties (**Ragasa *et al.*, 2013)**. Therefore, there is the need to update the status of improved rice varieties adoption and its contribution to rice output towards achieving food security and reducing poverty in rural Ghana. Hence, there is a need for this study.

Demand for rice is increasing as a result of rapid growth in population and changes in diet patterns. More than 90 percent of rice produced in the world is from South and East Asia with China being the leading producing country. For instance, about 501,201 thousand metric tons of rice produced globally in 2020/2021 is from South and East Asia. In Africa, 19,613 thousand metric tons of rice were produced in the 2020/2021 cropping season **(FAO, 2021)**. That is, Africa contributes approximately 4 percent to the global rice basket, meaning that Africa contributes abysmally to the world rice market. The reason is that there are poor marketing opportunities for rice producers in Africa, which leads to poor adoption decisions of improved rice varieties coupled with other agronomic practices among farm households. This makes Africa the net importer of rice from developed countries. High importation of rice to Africa increases governments' debt stock, which slows down economic growth and socio-economic transformation in the rural economy. There is therefore the need to boost rice production in Africa, particularly Ghana, to minimize rice importation through the adoption of improved rice production varieties.

The agricultural sector in Ghana is one of the pillars for sustainable economic growth and development. The sector has benefited from several interventions, particularly in the rice sector, to improve productivity, reduce poverty, and increase the incomes of farm households **(Ragasa *et al.*, 2013; GRA, 2020)**. Rice farm households in Ghana have been introduced to enhanced rice varieties in addition to other agronomic practices **(Langyintuo & Dogbe, 2005; Martey *et al.*, 2013)**. The aim of promoting green technologies such as high-yielding rice varieties is to increase rice production to meet domestic demand and also create market opportunities for farm households and other rice value chain actors. Increasing rice production and market opportunities have a positive impact on sustainable job creation in rural areas. However, rice production in Ghana is dominated by smallholder farmers who still largely depend on traditional rice varieties and agronomic practices for rice production. Smallholder farmers also depend on rainfall for rice production. These adversely affect rice production and productivity, which therefore lowers market opportunities for all rice value chain actors. In support of Ghana's dedication to enhance and sustain agricultural productivity, food security and facilitate the growth of the agricultural sector, the government of Ghana, has partnered with non-profit making organizations in promoting and disseminating improved rice varieties to farm households in order to enhance rice production and productivity **(McNamara *et al.*, 2014)**. The improved rice varieties disseminated to farm households in Ghana, particularly in northern Ghana, include Jasmine, AGRA, TOX, GR-18, Nerica, Mande, Digan, Afife, among others. Despite the dissemination of these improved rice varieties to farm households, rice farmers are still operating at low levels of productivity **(Langyintuo & Dogbe, 2005)** due to poor observation and usage of green revolution farming methods and technologies **(Azumah, 2019).** Rice projects mostly introduce improved rice varieties to farm households with high access to farm inputs and market opportunities. With these incentives, when improved rice variety is first released to farm households through a project, the adoption rate is high. When the rice projects end, rice farm households cease to have access to farm inputs and markets as well as other incentives. This leads to poor adoption and/or dis-adoption of improved rice varieties **(Lamptey, 2018)**. Most studies investigate the adoption of improved rice production technologies status when the projects are still ongoing or immediately the end of the project **(Lamptey, 2018; Obayelu, Dontsop, & Adeoti, 2016)**. This research sought to analyze the determinants of improved rice varieties adoption coupled with its contribution to rice output among farm households in the northern region of Ghana, by considering rice projects which have ended for over five years. The outcomes of this study would give policy directions to policymakers, along the rice value chain, to enhance rice productivity and incomes. The subsequent sections of this paper are organized into the literature review, methodologies, data collection and analysis, results and discussions, as well as conclusions and policy recommendations.

LITERATURE REVIEW

The term *adoption* refers to the full acceptance, use, and continuous use of a new idea or technology to enhance productivity **(Doss, 2006; Rogers, 2005).** It can also be defined as a unified, unique, and general phenomenon that is multifaceted with many inputs, actors, and consequences to improve productivity**.** In this study, adoption is considered as the degree of a rice farm household's usage of improved rice varieties, techniques, or phenomena to increase rice production and output. Farm households are inclined to adopt innovations that have positive effects on their rice production, income, and welfare as well as access to farm inputs and markets. Non-adoption of improved rice varieties among farm households is high when farmers have inadequate opportunities to access farm inputs and markets. Non-adoption of improved rice varieties can also occur when farmers feel that their traditional rice varieties perform better than the improved rice varieties.

Many studies have been conducted in the space of rice production technologies adoption and its impact on productivity (**Uaiene *et al.*, 2009; Muzari *et al.*, 2012; Bruce *et al.*, 2014; Wiredu *et al.*, 2014, 2010; Kasirye, 2013; Zakaria *et al.*, 2016; Abdulai *et al.*, 2018).** For instance, **Muzari *et al*. (2012)** reviewed studies on the impacts of innovation adoption among small-scale farmers in SSA. The authors' findings showed that adoption did not result in higher income of farmers as a result of land degradation, higher costs of fertilizers, production credit constraints, among others. However, **Kasirye (2013)** conducted a study on the bottlenecks to enhanced agricultural innovation usage in Uganda. The study found that the adoption of agricultural innovations has led to higher income and reduction of poverty among farm households. Similarly, the study revealed that adoption of enhanced agricultural innovations increased nutritional outcomes, reduced prices of consumable foods, and promoted job opportunities for rural Uganda. In Southern Ethiopia, assessing the adoption of numerous sustainable agricultural mechanisms and their effects on farm household earning was conducted by **Mohammed *et al.* (2015)**. The study demonstrated that the adoption of multiple sustainable agricultural mechanisms enhanced farm household income status. However, the study further revealed that multiple adoptions of sustainable agricultural mechanisms among farm household increases the cost of production but is relatively low for farm households whose selectively combined alternative mechanisms. In addition, the benefits of modern rice production innovations in smallholder farms have been well examined in Nigeria. It was found that about 98.6% and 91.5% of the smallholders achieved higher rice output and acquired new rice production skills respectively, due to the adoption of improved rice production technologies. It was also reported about 85.5% increase in rice income among rice farmers **(Adisa *et al.*, 2019)**. This demonstrates that the adoption of enhanced rice production technologies contributes positively to households' welfare and food security.

In Ghana, **Azumah *et al.* (2017**) studied the productivity effect of an innovation called urea deep placement among irrigation rice growers. The study found that the use of the urea deep placement enhanced rice yield, which would create jobs for rural dwellers. **Bruce *et al.* (2014)** likewise investigated the drivers and effects of enhanced rice variety adoption on rice output among rural farm households in Ghana. The study discovered that the use of improved rice varieties had a positive effect on rice farmers' output. The effect of NERICA rice variety adoption in Ghana was investigated by **Wiredu *et al.* (2014)**. The NERICA usage greatly enhanced rice income, farm incomes, per-capita income, and total annual incomes among rice farm households. The study recommended that there is a need to intensify NERICA promotion by creating farmers access to the improved rice seed. It also means efforts need to be made to provide markets and road infrastructure to facilitate rice farmers' access to farm resources and market outlets as well as services of extension agents.

The discussions above show that there have been several studies on the effects of adopting improved rice production technologies, to unlock rice production potential. However, these studies could not assess the adoption and effects of improved rice varieties on rice output using rice varieties that have been released to farmers over ten years (between 2009-2019 period). Against this backdrop, the study aimed at examining the determinants of improved rice varieties adoption and its effect on rice output in the northern region of Ghana. This study will add to the existing literature on the effects of the adoption of improved rice varieties and guide policymakers along the rice value chain to enhance rice production.

DATA AND METHODS

Profile of the study area

This study was conducted in the northern region of Ghana. The regional capital is located in the Tamale metropolis. The region is one of the largest regions in Ghana, covering an area of 70,384 square kilometers. The Northern Region is bounded to the North East Region to the north, Ghana-Togo international border to the east, the Oti Region to the south, and the Savannah Region to the west. The Savannah Agricultural Research Institute (SARI) is located in the region. SARI is among the thirteen research stations of the Council for Scientific and Industrial Research (CSIR) of this country. SARI is responsible for breeding improved rice and other crop varieties and disseminating them to farmers for adoption in other to enhance agricultural production in the northern part of Ghana.

The region is among the top first five regions massively into rice production in the country. Yet rice productivity is still below achievable yield due to poor adoption coupled with poor soil conditions, climate change, and high dependence on rain-fed farming **(Azumah, 2019; MoFA, 2016).** The wet season commences partly in April and augments from August to September but gradually secedes between October and November. The average annual precipitation stands between 750mm and 1050 mm, which is about 30 or 40 inches. Average temperatures are between 14 °C (59 °F) and 40 °C (104 °F) at night and day respectively. This is usually associated with a shorter wet season and less precipitation with a corresponding longer dry season and hot weather, which is unfriendly to rain-fed agriculture.

Sampling procedure, sample size, and data collection

Several sampling methods were employed to select the respondents from farming communities in the Northern Region of Ghana. The study area was purposively selected for this study because it is one of the leading rice-growing regions in the country. The region has a good environment that is favourable for rice production. The region alone contributed about 37% of rice output to the national food basket **(MoFA, 2020)**. A simple random sampling strategy, based on the lottery method, was employed to choose four districts in the region. The selected districts include Tolon, Kumbungu, Savelugu, and Nanton. Similarly, the simple random procedure by lottery method was also used to choose the rice-producing communities for the study. The selected rice-growing communities and their respective sample sizes were as follows: Nyankpala (29), Tingoli (29), Tolon (29) and Woribogu (29) in the Tolon District; and Botanga (28), Gbullung (28), Kpachi (28) and Kumbungu (28) in the Kumbungu District. The rest were Libga (30), Diare (30), Nabogu (30), and Savelugu (30) in the Savelugu Municipality while Nyamadu (31) and Nanton (31) were in the Nanton District. The sample size per selected community was derived from a sample frame obtained from the Northern Regional Directorate of MoFA, to form the total sample of 410 rice farmers for this study.

Scientifically, **Smith's (2019)** sample size formula was used to compute the sample size for this research. The formula involves a constant value of 95% confidence level, corresponding to a Z-score of 1.96, to determine the sample size, as shown in Equation 1.

$$Sample\ size\ (n) = (Z - score)^2 * Std\ Dev.* \frac{(1-Std.Dev.)}{(margin\ of\ error)^2} \quad (1)$$

Following Equation (1), the sample size computed for the study was 385 rice farmers. The study then adjusted the sample size to 410 to make room for lapses that might arise in the data collection and transmission process. After data cleaning, 404 questionnaires were found to be consistent and reliable for the analysis. Thus, primary data was mainly gathered using semi-structured questionnaires. The data was collected by 10 trained research assistants (graduates). They were all fluent both in the English language and the local dialects of the participating communities/districts. The data was collected between December 2019 and February 2020.

Analytical Framework: Propensity Score Matching Model

This study aims at examining the effect and determinants of improved rice varieties adoption on rice output in the northern region of Ghana. Since adoption is endogenously determined, examining the effect of improved rice varieties on rice output without addressing selectivity bias would give inconsistent and biased estimates which will lead to wrong policy recommendations. To remedy selectivity biases in data, we opted for the Propensity Score Matching **(**PSM) approach **(Rosenbaum & Rubin, 1983)**. Several stages followed to have robust estimates for the study. As part of the PSM approach, Logistic regression (logit) was first employed to examine the socioeconomic factors affecting improved rice varieties adoption among farm households. In the second step, a histogram was used to check for overlaps and common supports in the propensity score distribution. The third step was carried out to test the propensity score of the variables in the model. The fourth step was an overall quality test of factors before and after matching, while the final step estimated the effect of improved rice varieties adoption on rice output among farmers, using the average treatment effect model.

Propensity Score Matching and average treatment effect models

The PSM approach was first employed by **Rosenbaum & Rubin (1983)** as an econometric model to assess the effects of innovation on socio-economic outcomes. This method handles selectivity bias. This is because the selection of participants into programmes is often non-random and subject to sample selection bias.

PSM is used to analyse quasi-experimental data, to balance two non-equivalent groups on observable features, to get reliable estimates for the effect of improved rice varieties adoption for two groups **(Luellen *et al.,* 2005)**. The purpose of the analysis is to remove or at least reduce sample selection bias because a treated group (adopters) and a control group (non-adopters) in rice dissemination technologies projects are often different without any treatment. With the help of PSM, the selection bias can be removed, which would assist in actually estimating the actual impact of improved rice varieties adoption on rice output for adopters, which can be ascribed to the projects promoting improved rice production in the study area **(Caliendo & Kopeinig, 2008)**.

Against this backdrop, the study employed PSM to form a group for comparisons depending on the likelihood model of adoption or non-adoption of improved rice varieties. Farm households who adopted the improved rice varieties are compared with non-adopters based on chance (propensity scores). The real effect of improved rice varieties adoption is computed as the average difference in rice output per hectare of the adopters and non-adopters. This was achieved after comparing the individuals with similar features for both adopters and non-adopters.

For the empirical estimation, the binary choice logistic regression was first employed to estimate the propensity score of every farm household-head as the tendency to adopt improved rice varieties. Propensity scores were estimated with farm households and farm features using adoption as a dependent variable (**Deschamps & Jean, 2013; Djido *et al.*, 2013)**. The propensity score (PS) model of adoption is represented mathematically with Y as the likelihood of a farm household adopting at least one or more improved rice varieties and X as the set of covariates, which influence adoption decision (Equation 2).

$$PS = P_r\left(\frac{1}{X}\right) = (b_0X_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + \cdots b_{15}X_{15} + \mu) > 0 \quad (2)$$

Where: Xs are socioeconomic variables expecting to be influencing rice farmers' adoption of improved technologies, bs are the logistic coefficients to be estimated and μ denotes the random white noise capturing measurement errors and unobservable factors influencing adoption.

The essence of PSM is to help compare the observed outputs of improved rice variety adopters and non-adopters depending on the predicted chance of adopting at least one variety **(Wooldridge, 2005; Heckman *et al.*, 1998)**. The Average Treatment Effect (ATE) for adoption on rice output is then estimated in consonance with the propensity scores determined with the logit model. The ATE is the average difference in rice output between adopters, which is represented by $[Y(1)]$ and non-adopters, represented by$[\,Y(0)]$. The model for estimation of the ATE is symbolically denoted by Equation (3).

$$ATE = E[Y(1) - Y(0)] = E[Y(1)] - E[Y(0)] \quad (3)$$

The ATE model seeks to compare the rice output of farm households who continue to use at least one improved rice variety, with the output of non-adopters. It serves as a control for farm households with similar noticeable features and partial control for non-random selection of members in the adoption of improved rice varieties. The ATE output is interpreted as the effect of the improved rice variety adoption on rice output. An average treatment effect on the treated (ATT) is likewise estimated, besides the ATE. The ATT model is used to measure the effect of adoption on the output of only actual adopters of the improved rice varieties, and not those of potential adopters, non-adopters, initial adopters, or dis-adopters. The ATT can be computed as Equation (4).

$$ATT = E\left[Y(1)\frac{Y(0)}{D} = 1\right] E\frac{[Y(1)]}{D} = 1\ E\left[\frac{Y(0)}{D} = 1\right] \quad (4)$$

Where: E is a dummy variable or indicator for treatment (D = 1 for adopters, 0 for non-adopters). The average treatment effect on the untreated or control categories (ATC) is estimated to measure the effect of adoption on output for non-adopters of the improved rice varieties. The model for this parameter is measured by Equation (5).

$$ATC = E\left[Y(1)\frac{Y(0)}{D} = 0\right] E\left[\frac{Y(1)}{D} = 0\right]\ E\left[\frac{Y(0)}{D} = 0\right] \quad (5)$$

Previous empirical studies that used the PSM model have shown and emphasized that the outcomes are based essentially on precision and approaches employed for the matching **(Imbens, 2004; Caliendo & Kopeinig, 2008)**. This study employed different specifications and matching approaches to check for robustness in its empirical work. The matching strategies mainly employed in PSM methods include the Kernel-Based Matching (KBM) and the Nearest Neighbour Matching (NNM). Results of the Regression Adjustment Method (RAM) were thus included in this work to compare three different estimation methods, to check for sensitivity.

Definition and measurement of variables and their a-priori expectations

Table 1 illustrates the variable description, measurement of variables, and a-priori expectations. The expected effects of each variable on adoption are also presented in Table 1.

RESULTS AND DISCUSSIONS

Descriptive Statistics of Selected Variables

The results of socio-demographic factors of the rice farm households are presented in Table 2. The study found that about 46% of the rice farm households continued to use the improved rice varieties in the study area. This implies that the majority of rice farmers are not using the improved rice varieties. That could lead to low rice production and productivity, which could worsen food insecurity and poverty among rice farm households.

Table 1: Definition of variables, measurements, and their *a-priori* expectations

Variables	Definitions	Measurements	A-priori expectations
Adoption	If a farmer ever adopted improved rice variety and continues using it.	Dummy: (1) Yes (0) No	N/A
Rice output	Amount of rice harvested per hectare	Kg	N/A
Age	Age of a rice farmer.	Years	+/-
Gender	Sex of a rice farmer.	Dummy: (1) Male (0) Female	+/-
Education	The number of years a farmer attended formal school.	Years	+
Family labour	The total number of family labour used in rice production.	Number	+/-
Electricity	A rice farmer household has access to electricity.	Dummy: (1) Yes (0) No	+/-
FBOs	A rice farmer belongs to the rice farmers' association.	Dummy: (1) Yes (0) No	+
Mobile phone	Rice farmer has his/her phone for communication.	Dummy: (1) Yes (0) No	+
Input market	A rice farmer has access to the input market in the community.	Dummy: (1) Yes (0) No	+
Credit	A rice farmer has access to a production credit.	Dummy: (1) Yes (0)No	+
Extension service	A rice farmer had access to an extension advisory service in the 2019/2020 cropping calendar	Dummy: (1) Yes (0)No	+
Farm area	Rice farm plot area of a farmer.	Hectare	+/-
Rice policy	A rice farmer is aware of any government rice policy in Ghana.	Dummy: (1) Yes (0)No	+
Field Demo	A rice farmer ever participated in a rice production field demonstration	Dummy: (1) Yes (0) No	+
Mechanization	Farmer has access to tractor service and used it for ploughing rice fields.	Dummy: (1) Yes (0)No	+
Rainfall perception	A rice farmer's perception of rainfall pattern.	Dummy: (1) decreased (0) increased	+

The reasons for non-adoption of improved rice varieties include (1) poor access to farm inputs and output market; (2) pests and diseases; (3) lack of access to production credit; (4) taste and aroma of rice varieties; and (4) high demand of labour for adopting rice varieties and its agronomic practices after the end of the rice projects. One of the respondents said: "I wanted to cultivate Jasmine rice variety when it first came to our community. However, I realized that it is less resistant to pests and diseases. These made me not to plant the variety and maintained my local rice varieties".

Another rice farmer argued: "When non-governmental organizations and Ministry of Agriculture are coming to implement improved rice variety adoption projects, the projects come with access to farm inputs and ready markets for outputs. When the projects end, it is difficult for us to access farm inputs and markets for our paddy rice. These discourage us from continuing to use improved rice varieties when the projects end". This confirms the fact that rejection of innovation is possible at any stage of the adoption process (**Rogers, 2003**). The average yield of a rice farmer was found to be 1438.9kg/hectare (1.44mt/ha), equivalent to 14.4 maxi bags (100kg each) of rice per hectare in the study area. This was far below the national average rice yield of 2.96mt/ha reported by MoFA (2019). The low yield could be attributed to poor adoption of rice production technologies among farmers.

Table 2: Descriptive statistics of variables

Variable	Mean	Std. Dev.
Adoption/non-adoption	0.46	0.50
Rice output	1438.90	1775.55
Age	39.69	10.65
Gender	0.90	0.30
Education	0.29	0.46
Electricity	0.80	0.40
Family labour	5.63	8.80
FBOs	0.47	0.50
Mobile phone	0.25	0.43
Field demo	0.62	0.49
Input market	0.85	0.36
Production credit	0.35	0.48
Extension service	0.80	0.40
Farm plot area	1.55	1.53
Government policy	0.87	0.34
Mechanization	0.78	0.41
Rainfall perception	0.92	0.28

Source: Survey Data, 2020: 1bag = 86 kg (MoFA conversion chart)

In addition, the mean age of a rice farmer was approximately 40 years with a corresponding mean formal education being 3 years. This means the rice farmers were predominantly in their youthful years with little education, which could translate into real adoption/usage of improved rice varieties. Meanwhile, formal education among rice farmers was still low, which resulted in the non-adoption of rice production technologies. **Martey *et al.* (2013)** revealed that farmers with formal educational backgrounds are more prone to the adoption of improved agricultural technologies since they tend to co-operate favourably with other farmers' development organizations. The family labour and mean farm size of the rice farmers were approximately 6 people and 0.65 ha respectively. The little higher use of family labour means that rice farmers can rely on family labour to reduce the cost of production when adopting new rice varieties. The low average rice farm size (1.55 hectare) of the farmers confirmed **MoFA (2016)** findings that about 90% of smallholders cultivate less than 2 Ha in Ghana. The study further revealed that about 90% of the respondents were males, meaning that rice is predominantly produced by men in Northern Ghana. The low percentage of female farmers in this study corroborates **Martey *et al.* (2013)** who asserted that females were normally occupied with domestic activities such that they did not have enough time to participate in Rice Development Projects (RDP) compared to their male counterparts. Rice farmers' awareness of government policy about rice production plays a critical role in technology adoption to enhance rice production and productivity. The study demonstrated that about 87% of rice farmers were aware of government policy for the rice sector. This will influence farmers positively, especially the youth, to make rice production a business instead of conventional farming. Also, about 62%, 85%, 80%, and 35% of rice farmers had access to field demonstration, input market, extension services, and production credit respectively. These imply that rice farmers' ability to access agricultural extension services, farm inputs, and participation in rice field demonstrations were high but they had less access to production capital. About 92% of rice farmers perceived a decrease in the rainfall pattern for the past ten years, 75% had access to a good road network, 47% belonged to FBOs, 25% owned mobile phones, and 78% practiced mechanization (used tractor for land ploughing).

Factors affecting improved rice variety adoption

This section discusses socio-demographic factors which influence farm households' decision to adopt improved rice varieties. The results are presented in Table 3. Although the Pseudo R-Squared value was low at 0.1840, the Chi^2 test statistic value (101.38) was highly significant at the 1% level. This is an indication that the logit model (PSM approach) was best fit for the estimation. Eight (8) out of the 15 explanatory variables were significantly influencing farm households' adoption decision of improved rice varieties in the study area. These include age, family labour, membership to FBOs, input market, mobile phone, rainfall perception, mechanization, and government rice policy.

The study found that age had an inverse relationship with improved rice variety adoption, which was averagely significant at a 5% level. The inverse relationship of age to adoption meant that younger rice farm households had a higher propensity to adopt improved rice varieties than older farmers. This is plausible since younger farmers tend to be more innovative than their older counterparts (Rogers, 2005). Older farmers are more risk-averse, sceptical, and conservative when it comes to adopting innovations. These could make older rice farmers not innovative to adopt improved rice varieties, especially when they are not yet tested or tried improved rice varieties. Older farmers may also fail to adopt improved agricultural technologies based on their experience. This finding corroborates **Martey *et al.* (2013)** and **Ragasa & Chapoto (2017)** on the adoption of agricultural technologies in Ghana. However, it contradicts the finding of **Azumah & Zakaria (2019)** that age had a positive effect on farmers' usage of chemical fertilizers in Ghana.

Family labour had a positive effect on farm household adoption behaviour of improved rice varieties and it was statistically significant at a 10% level. This implies that rice farm households who depend on family labour have a high probability to continue using improved rice varieties than those who depend on hired labour. Labour-intensive technologies stand the risk of being non-adopted by rice farm households who depend on hired labour for their adoption. However, labour-intensive agricultural technologies can easily be adopted by farm households with relatively large family labour. **Ehiakpor *et al.* (2019)** found that farmers who used family labour had a higher tendency of adopting the *Zai* farming innovation method in Ghana than those who did not. Similarly, **Azumah & Zakaria (2019)** found a positive effect of family labour on farmers' participation in fertilizer subsidy programmes in Ghana.

Membership to FBOs in the study had a positive effect on the adoption of improved rice varieties, which was significant at a 5% level. This implies that rice farm householders belonging to rice farmers' associations (FBOs) have a high chance to continue using improved rice production technologies compare to those who do not belong to rice farmers' associations. FBOs strengthen social capital, which encourages farmers to continue the use of modern production technologies. Farm households who do not belong to any farmers' association easily reject improved agricultural technologies since there is nobody to motivate them to use the modern production technologies. However, farm householders who join FBOs, assist each other to adopt green revolution technologies to enhance productivity and income. Adoption of labour-intensive technologies by farm households becomes easier when belonging to farmers' associations. It has been argued that FBOs help in linking farmers to input sources and product markets as well as to important resources like extension advisory services alongside farmer field schools, or field demonstrations **(Zakaria *et al.*, 2020).** This suggests that farm householders will be associating themselves with FBOs which have the potential to stimulate their ability to continue using improved rice production technologies. According to **Ojoko *et al.* (2017),** being a member of farmers' associations in a geographical area influences a farmer's access to agricultural technical inputs and markets. These open an opportunity for farmers to enhance farmer-to-farmer-transfer of agricultural technologies, which is the quick way for technology dissemination.

Furthermore, access to the inputs market yielded a positive effect on the adoption of improved rice varieties and it was highly significant at a 1% level. The positive significance implies that rice farmers with access to input markets like fertilizers, weedicides/pesticides, and improved seeds in the community or nearby community are more likely to continue using improved rice production ideas than other farmers. This can also be interpreted to mean that rice farmers having less access to input markets are quite likely to reject rice production ideas. This is probable since the additional cost of traveling to input markets far from their communities serves as a disincentive to the farmers who would genuinely love to use new rice varieties. As result, poor access to inputs markets by farmers makes them resort to the cultivation of the traditional rice varieties that have low input requirements. Making farm inputs accessible to farmers tends to strengthen sustainable adoption of enhanced farming innovations, especially in cereal food crop production. Since agricultural technology adoption is the cornerstone to combat food insecurity and poverty outcomes, access to farm inputs in farmers' communities or nearby communities is critical.

Ownership of mobile phones assists farm households to access agricultural-related information. Mobile phone ownership was found to have a positive effect on the adoption of improved rice varieties. This was statistically significant at a 1% level in the study. That is, a farm household with a cell phone is very likely to continue the use of improved rice varieties and access agricultural information. It has been argued that mobile phone technology assists farmers to access and uptake improved agricultural technologies **(Chimoita *et al.*, 2017; Azumah, Zakaria, & Boateng, 2020).** Perception of rainfall had a positive and significant effect on the adoption of improved rice varieties at a 1% level. This implies that a perceived decrease in rainfall influences rice farmers to enhance their continued use of improved rice varieties. That means farmers who perceived a decrease in the intensity of rainfall in recent years had a higher probability of adopting and/or continued the use of improved rice varieties than those who thought otherwise. This outcome is supported by **Zakaria *et al.* (2020a)** that perception of decreased rainfall positively influenced farmers' decision to adopt climate-smart mechanisms in Ghana.

Mechanization in the study was found to have a negative effect on the adoption of improved rice varieties, which was significant at a 1% level. This explains that rice farm households who do not have access to tractor services are more likely to reject improved rice varieties. Access to tractor service by farm households assists them to practice large-scale rice farming, which also aids farmers' adoption of improved rice varieties, to enhance productivity. Less access to tractors for rice cultivation will force farmers to continue in small-scale farming and non-adoption of improved rice varieties, which they used to practice. In Pakistan, **Ullah *et al.* (2018)** found mechanization to have a positive effect on the adoption of improved agricultural cultivars. The last variable of interest is rice farmers' awareness of government rice policy, which had a positive significant effect on improved rice variety adoption at a 1% level. This implies that farmers who are aware of government policy about rice production are more likely to adopt and/or continue to use improved rice cultivars. Communication of government policy about rice production to farmers through MoFA and other media will boost their decision to adopt new rice cultivars to enhance rice production and productivity. Lack of farmers' awareness of government policy for rice production is a potential threat to the adoption of rice new cultivars and production. Hence, farmers need to be considered when designing and implementing government policy about the rice sector.

Propensity score test of variables in the model

The propensity score test results of variables in the model, consisting of real adopters (treated) and non-adopters (control) rice farm households, using both the matched and unmatched samples are presented in Table 4. The average age of the real adopters (from the treated households) was about 41 years while those of the non-adopters (from the control households) were found to be 39 years. The age difference between the two households is statistically significant. **Zakaria *et al.* (2019)** also found a significant difference between the average age of farmers from livelihood diversified households (40 years) and those from non-livelihood diversified households (39 years). Similarly, **Dagunga *et al.* (2020)** found that adopters and non-adopters of farming innovations in the Northern Region were younger than their fellow farmers who live within the Upper East of Ghana.

About 89% of the adopters were males while 91% of their non-adopter counterparts were also males, corroborating **Ragasa *et al.* (2013)** and **APS (2015)**. About 76% of the adopters in both the matched and unmatched samples had access to electricity while about 72% and 80% of the non-adopters in the matched and unmatched samples respectively had no access to electricity. Farmers' inability to access electricity hinders their adoption of agricultural innovations. The mean level of education of treated and control farm households were both about 3 years, which was very low and in tandem with **Dagunga *et al.* (2020)** and **Mahama *et al.* (2020)**.

In addition, the results have shown that all farmers in the region over-rely on family labour. About 58% of the adopters in both the matched and unmatched samples belonged to FBOs whereas only 54% and 32% of the non-adopters in the matched and unmatched samples respectively belonged to FBOs. There were therefore statistically significant differences between adopters who belonged to FBOs and their non-adopting counterparts. A good number of both the adopters (44%) and non-adopters (41%) in the region had access to credit. Having access to credit enhances the adoption of agricultural innovations but the results of this study showed that more than 50% of the farmers in the region lacked access to credit, because they were risk-averse.

Most of the adopters (85%) in both the matched and unmatched samples are accessible to extension services. Farmers' ability to obtain extension services facilitates their adoption of farm technologies. However, the non-adoption of improved rice varieties in the northern region of Ghana, despite farmers' greater access to extension services, implied that most of the farmers did not take advantage of extension services at their disposal, to harness their adoption potentials. The results further showed that most of the treated farm households (over 85%) had access to input markets in their communities, with an average farm size of about 2 acres. More adopters (36%) had access to telephones than non-adopters (11%), which may explain the rationale for their adoption decisions. More than half of the adopters (53%) attended field demonstrations. Participation in field demonstrations increases farmers' chances of adopting improved rice varieties promoted by agricultural extension officers. **Dagunga *et al.* (2020)** also found that only 26% of adopters attended field demonstrations. Almost all the farm households (about 98%) in Northern Ghana noticed a decrease in the rainfall pattern in the last ten years. It means both adopters and non-adopters suffered the effects of climate change on their rice farming. Similarly, a large number of the farmers (over 74%) had access to mechanization services, meaning mechanization is a necessity in rice farming compared to maize that can be conveniently cultivated under zero tillage. Finally, over 80% of the farmers were aware of government policies aimed at increasing domestic rice production in Ghana. However, more adopters (91%) than non-adopters (81%) were aware of these policies, meaning more efforts should be made to educate all rice farmers on government policies in aid of boosting rice production and enhancing food security in this country.

Overall quality test of factors before and after matching

Table 5 reports the summary statistics of the overall quality test of factors before and after matching. The mean bias of the unmatched (adopters) and matched (non-adopters) were 108.6 and 55.4 respectively. Both means were significant at 10%, meaning there was selection bias of either adopters or non-adopters of improved rice varieties in the region. The percentage reduction of bias in the sample was 48.98%.

Overlapping and common support in the propensity score distribution

Observed dissimilarities in characteristics between adopters and non-adopters of improved rice seed varieties were checked using the PSM approach. The observed differences between treated (adopters) and untreated (non-adopters) were detected using the common support region. The minima and maxima were used to figure out the validity of the common support region (**Smith & Todd, 2005; Caliendo & Kopeinig, 2005**). The matching distribution of the propensity scores after matching for treated and untreated are shown by the histogram in Figure 1. The lower part of the figure shows the propensity score distribution for the non-adopters, and the upper part represents the adopters. The densities of the scores are on the y-axis. A closer look at the figure reveals that the common support region is a well-balanced match for the entire sample. This signifies adequate overlap between the two groups and implies that the matching has produced counterfactuals that are statistically related to the adopters. The findings are consistent with those of **Zakaria *et al.* (2019), Martey *et al.* (2015),** and **Elias *et al.* (2013).**

Table 3: Maximum likelihood estimation of the factors affecting improved rice variety adoption

Variable	Coef.	Std. Err.	Z	Marginal effect	Std. Err.	Z
Age	-0.013**	0.007	-1.960	-0.005**	0.003	-1.960
Gender	-0.220	0.242	-0.910	-0.083	0.088	-0.940
Electricity	-0.198	0.181	-1.090	-0.076	0.068	-1.110
Education	-0.015	0.016	-0.950	-0.006	0.006	-0.950
Family labour	0.049*	0.029	1.680	0.019*	0.011	1.680
FBOs	0.351**	0.157	2.240	0.135**	0.059	2.270
Credit	-0.099	0.140	-0.710	-0.039	0.054	-0.710
Extension	0.263	0.177	1.480	0.103	0.070	1.470
Input market	0.721***	0.223	3.230	0.282***	0.083	3.390
Farm size	0.039	0.024	0.600	0.015	0.009	1.600
Mobile-phone	0.753***	0.193	3.910	0.270***	0.061	4.450
Field Demo	0.244	0.154	1.580	0.094	0.059	1.590
Perception of rainfall	0.747**	0.323	2.310	0.290***	0.116	2.500
Mechanization	-0.424**	0.180	-2.350	-0.158***	0.063	-2.490
Government rice policy	0.481**	0.204	2.360	0.190**	0.080	2.380
cons	-1.021*	0.571	-1.790			
Model diagnosis						
The number of obs.	404					
LR chi^2 (15)	101.38***					
Prob > chi^2	0.0000					
Log likelihood	-224.86849					
Pseudo R2	0.1840					

* represents 10%, ** represents 5%, and *** represents 1% levels of significance.
Source: Survey data, 2020

Table 4: Propensity score test of variables in the model

Variable	Unmatched(U)	Mean				t-test	
	Matched(M)	Treated	Control	% bias	% red. Bias	T	p>t
Age	U	39.263	40.942	-15.800	42.200	-1.570	0.1160
	M	39.263	40.233	-9.100		-0.990	0.323
Gender	U	0.888	0.919	-10.400	43.800	-1.020	0.309
	M	0.888	0.905	-5.800		-0.610	0.543
Electricity	U	0.763	0.797	-8.100	-15.500	-0.800	0.424
	M	0.763	0.724	9.300		0.960	0.340
Education (years)	U	2.578	2.791	-4.500	-419.800	-0.450	0.652
	M	2.578	1.470	23.400		2.850	0.005
Family labour	U	1.987	1.247	27.900	15.000	2.750	0.006
	M	1.987	1.359	23.700		2.590	0.010
FBOs	U	0.578	0.320	53.500	83.300	5.300	0.000
	M	0.578	0.534	9.000		0.930	0.351
Credit	U	0.444	0.453	-1.900	-669.500	-0.190	0.850.
	M	0.444	0.371	14.700		1.610	0.109
Extension	U	0.853	0.721	32.700	74.000	3.310	0.001
	M	0.853	0.888	-8.500		-1.110	0.269
Input market	U	0.888	0.797	25.200	52.900	2.550	0.011
	M	0.888	0.845	11.900		1.360	0.173
Farm size	U	1.780	1.058	26.400	-149.500	2.680	0.008
	M	1.780	3.582	-65.900		-3.080	0.002
Telephone	U	0.362	0.105	63.700	98.300	6.140	0.000
	M	0.362	0.358	1.1		0.100	0.923
Field Demo	U	0.526	0.320	42.600	89.500	4.210	0.000
	M	0.526	0.504	4.4		0.460	0.643
Rainfall perception	U	0.978	0.890	36.300	95.200	3.800	0.000
	M	0.978	0.983	-1.800		-0.340	0.737
Mechanization	U	0.741	0.843	-25.200	91.500	-2.470	0.014
	M	0.741	0.750	-2.100		-0.210	0.832
Government policy	U	0.909	0.814	27.900	72.900	2.830	0.005
	M	0.909	0.884	7.5		0.910	0.361

Source: Survey data, 2020

The effect of improved rice varieties adoption on rice output

Table 6 presents the estimates of the effect of improved rice varieties adoption on rice output among farm households. All the coefficients for ATT, ATE, and ATC for the estimators employed for examining the effect of adoption of improved rice varieties was statistically significant except nearest-neighbour matching for the average treatment effect on the control (ATC). These imply that future projects for rice production are more likely to enhance rice production and productivity. This is plausible, if the prevailing climatic, environmental, and socio-economic factors hindering adoption are removed or held constant. The propensity score matching was significant at 1% for the average treatment effect (ATE), the average treatment effect on the treated (ATT), and the average treatment effect on the control (ATC). This means that other things being equal, farm households' rice output will increase if they adopt improved rice varieties. It confirms that adopters of improved rice varieties are better off than non-adopters. Specifically, the coefficients for NNM, PSM, IPW, and RA for ATE were approximately 4.2, 7.7, 8.2, and 8.8 respectively, which were significant at different levels. These suggest that adopters of improved rice varieties improved from 4.2 kg/ha to 8.8 kg/ha compared to the non-adopters. This implies that adopters' rice output improved by about 52.3%.

The coefficients for the estimators NNM, PSM, IPW, and RA for ATT include 5.3, 8.4, 7.7, and 8.5 respectively and they were all significant at 1% and 5% levels. The ATT estimates the impact of adopters only. The positive significant coefficients for the ATT imply that the adoption of improved rice varieties led to higher rice output. That is, actual adopters' rice output increased from 5.3 kg/ha to 8.5 kg/ha. The ATC measures potential adopters of improved rice varieties. The coefficients for ATC for PSM and NNM were estimated to be approximately 6.8 and 2.6 respectively. This implies that if the non-adopters had adopted they would have had higher rice output compared to their non-adoption condition.

Table 5: Overall quality test of factors before and after matching

Sample	Ps	R2	LR	chi2	p>chi2	Mean Bias	Percentage reduction of bias
Unmatched	0.184	101.380	0.000	26.800	26.400	108.6*	48.98
Matched	0.057	36.350	0.002	13.200	9.00	55.4*	

Source: Survey data, 2020. * indicates significance at 10%

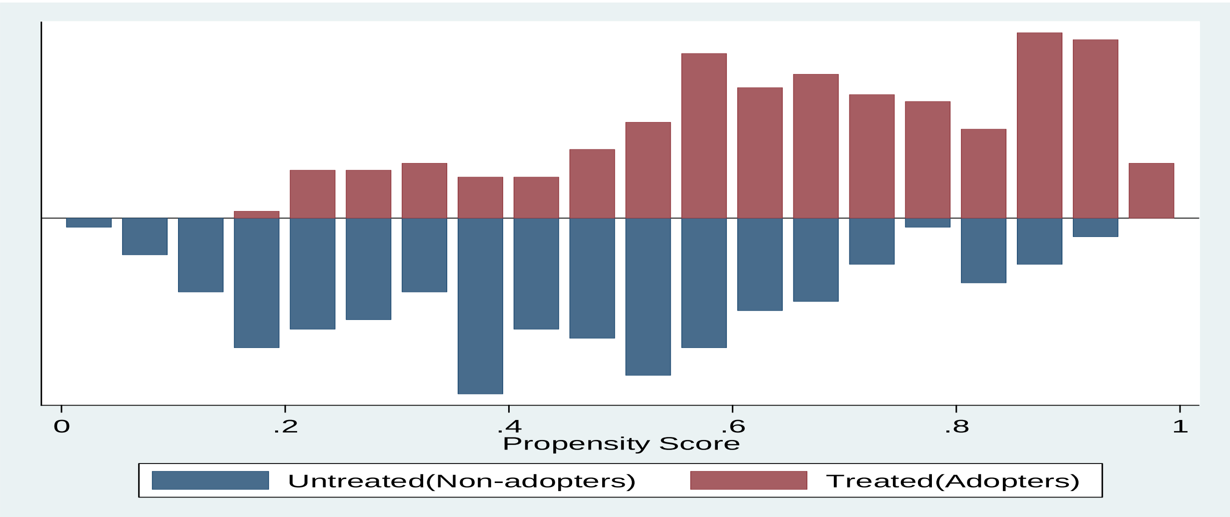

Figure 1: Propensity score distribution
Source: Survey data, 2020

Table 6: Estimated impact of improved rice variety adoption on rice output

Estimator	ATE	Treatment status ATT Coefficient (Std. Err.)	ATC
Propensity score matching (PSM)	7.705*** (1.763)	8.390*** (2.478)	6.782*** (2.549)
Nearest-neighbour matching (NNM)	4.151** (1.805)	5.321** (2.378)	2.573 (1.649)
Inverse-probability weights (IPW)	8.209*** (2.779)	7.710** (3.446)	
Regression adjustment (RA)	8.844*** (2.015)	8.481*** (2.255)	

Source: Survey data, 2020.
*** indicates significance at 1% and ** indicates 5% respectively

The positive significant effects of all the estimators for the ATE, ATT, and ATC demonstrate that adoption of improved rice varieties have a positive impact on productivity. Higher productivity of rice as a result of the adoption of improved rice varieties will increase farm household's income, reduce food insecurity, and poverty among resource-poor farm households in Ghana, as well as the whole of SSA. The findings are in tandem with those of **Martey *et al.* (2015), Abate *et al.* (2013),** and **Elias et al. (2013)**. Generally, the positive impact could be ascribed to the demonstration plots of MoFA on practices relating to the adoption of improved rice varieties and access to input markets, among others, in the region. These benefits served as incentives to improve farm households' adoption of improved rice varieties and their related agronomic practices to maximize output. The result justifies investment in agricultural innovation dissemination projects to increase improved rice variety adoption levels among farm households in Ghana and other parts of SSA to ensure maximum rice output to enhance the welfare of smallholder farmers.

CONCLUSIONS AND RECOMMENDATIONS

This study used the propensity score matching (PSM) model to examine the drivers and effect of improved rice variety adoption on rice output in the northern region of Ghana. Multistage sampling techniques were employed to collect data from 404 rice farm households in the study area. The empirical results reveal that adoption of improved rice varieties by farm households contribute positively to rice output. This could translate into reducing food and nutrition insecurity and the importation of rice into Ghana. The adoption of improved rice varieties is positively affected by family labour, membership in FBO, temperature, awareness of government policy, telephone ownership, and closeness to input markets. However, the adoption of improved rice varieties bears a significant negative relationship with the age of the farmer and mechanization. To enhance rice productivity and food security outcomes, it is recommended that the development of enhanced rice varieties, dissemination, and promotion of the varieties should be given priority among stakeholders along the rice value chain. Farmers should be entreated to join/form FBOs and support their farm work with family labour to maximize rice output. Access to market by farmers should be created or enhanced by improving rural road networks, especially in the rural areas where rice production is eminent. Government policy about rice production should be well designed and communicated to rice farmers since awareness of government rice policy leads to an increase in improved rice variety adoption. Finally, the government of Ghana should subsidize mechanization services for rice farmers to help decrease their costs of production and to maximize output.

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PARTNERSHIPS AND CHOICE OF MARKET OUTLETS AMONG BEANS FARMERS IN KENYA

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ABSTRACT

Research background
Beans form a substantial part of the household diet in East and Central Africa and are consumed by most households. They are alternative low-cost proteins for less endowed people in a society and can contribute towards nutrition, food security, and employment. In Homa Bay County, beans are staple food grown by a vast majority of farmers. Choice of market outlet is the most significant decision for farm households to sell their produce to the different market outlets, which has a more substantial impact on household income.
Purpose of the article
Factors influencing the choice of market outlets among smallholder bean farmers in Homa Bay County, Kenya
Methods
Data collected were analyzed using a Multivariate Probit. Multi-stage sampling was used to collect data from 362 farmers, which constituted 181 participants and 181 non-participants of Public-private partnerships (PPPs); data was collected using a pretested semi-structured questionnaire.
Findings & value added & novelty
The market outlet choices available in the study area for sales of beans included consumers, brokers, retailers, and wholesalers; however, retailers and wholesalers constituted more than half of the market outlets. Experience in bean farming, farm size, access to training, credit, and partnership participation positively and significantly influenced selling to these market outlets. Farmers who participated in PPP participated more in bean farming than non-participants; this might be attributed to the benefit acquired from partnerships, such as training farm inputs, among others. Thus, PPP could be an effective way of improving smallholder livelihood; policies that include mechanisms that create or secure markets for smallholder farmers will see to it that they get increased returns.

Keywords: market outlets; multivariate probit; public-private partnership; smallholder farmers
JEL Codes: P32; Q13; M31

INTRODUCTION

Common bean (*Phaseolus vulgaris* L.) is the world's most important legume for human consumption (**Katungi *et al.*, 2010).** In Kenya, consumption of beans contributes relatively high to human nutrition; the per capita consumption is estimated at 14kg per year but can be as high as 66kg/year in western parts of the country (**Buruchara 2007; Katungi *et al.*, 2010).** There has been increasing demand for beans as a source of proteins in Kenya, although their consumption has been constrained by supply. This deficit is expected to rise given the population increase and health-conscious consumers shifting to plant proteins. This has called for different measures by different actors to help scale up the supply of bean grain by farmers. In Kenya, beans are grown mainly by small-scale farmers with less than 5 acres and are usually intercropped with maize. The crop is grown in almost all regions in Kenya; However, Eastern, Nyanza, Central, Western and Rift valley are the major bean-growing provinces. Regarding bean outputs, rift valley leads with 33 %, Nyanza and western are ranked second and account for about 22 % of national production while Eastern part and Coast regions outputs are constrained by adverse climatic conditions (**Katungi *et al.*, 2010)**. Beans are a staple food in Homa Bay and are grown by a vast majority (80%) of farmers across the County **(GoK, 2013).** According to **KALRO (2015)**, Homa Bay County beans per capita consumption has increased from 29.7 kg since 1999 to over 59 kgs in 2015. This compares to the western region's consumption level at 66 kgs per capita. The objective of this study was to analyze factors influencing the choice of market outlets among smallholder bean farmers in Homa Bay County.

Public-Private Partnerships (PPP) are broadly promoted as having the potential to help modernize the agricultural sector and deliver multiple benefits that can contribute towards sustainable agricultural development that is inclusive of smallholder farmers (**WEF, 2011; WEF, 2013). Chandan *et al.* (2017)** defined PPP as a collaborative effort between the public and private sectors contributing to various functions to achieve partners' goals. Public-Private Partnership is an effective way to capitalize on the relative strength of public and private sectors to address problems that neither could tackle adequately on its own **(Rankin *et al.*, 2016).** Creating a PPP entity with well-defined objectives can create a win-win collaborative arrangement whereby both commercial and developmental goals are achieved, besides promoting the inclusion of smallholder producers in developing countries. However, public-private partnerships are effective ways for the public and private sectors to collaborate and improve agricultural sustainability in developing nations (**Chandan *et al*., 2017).**

Public-private partnerships supplement scarce public resources, improve efficiency and reduce cost, thereby creating a more competitive environment. This study included farmers engaging in bean farming, both participants and non-participants of PPP intervention in Homa Bay County. According to **(Ugen *et al.*, 2017),** the PPP approach is an intervention to help bean farmers with seed credit, some advanced refinancing arrangements, capacity building, and a structured market system. Two partnerships were studied in this study, the major partnership was between farmers and pre-cooked bean partners, and the second partnership was between one-acre fund and the farmers. Public-private partnership in a pre-cooked bean value chain was established in order to enhance the capacity of smallholder farmers to supply seed and grains; the partnership had multiple players such as grain traders, research institutions, farmer groups, aggregators of the bean, financial institutions, local government, seed companies, NGOs, Media, Caritas, Kenya Agricultural and Livestock Research Organization (KALRO), agro-dealers, processor and a law enforcement agency **(Ugen *et al.*, 2017).**

The major partners were Kenya agricultural and livestock research organizations who developed bean varieties suitable for the pre-cooking process. The seed varieties were later distributed to Caritas, who then distributed them to targeted farmers' groups in different Sub-counties in Homa Bay. In addition, CARITAS mobilized farmers into groups, provided extension services, training, and credit. The improved bean seeds were also taken to agro-dealers who stocked them and sold them to farmers. Alliance of Biodiversity International and the International Center for Tropical Agriculture (CIAT) were in charge of technology development and capacity building in the PPP. The last partner was the lasting solution and collected graded beans for processing; the Processors, however, bought beans from the open market and very minimal quantity from farmers in the study area. The pre-cooked bean value chain was based on institutional PPP, where partner interaction and the parties are the most crucial feature **(Andersen, 2004; Brinkerhoff & Brinkerhoff, 2004).** Institutional PPP is the most preferred since it is not complex as a contractual PPP and has simpler contract modalities such as the memorandum of association **(Klijn & Teisman, 2003).** One Acre Fund has been involved in supplying smallholder farmers with farm inputs, credit, in addition to providing extension services and training.

LITERATURE REVIEW

Bean is one of the potential legume crops produced in Homa Bay County; this makes a substantial contribution to the livelihood and income of small-scale farmers in the area. Farmers can sell beans via multiple outlets in order to maximize expected utility, making a firm decision. According to **Shewaye (2016),** market outlet choice is the most significant decision for farm households in selling their produce to the different market outlets, which has a more substantial impact on household income. Choice of the market outlet is a household-specific decision, and various factors are considered to be the basis for such a decision. Past studies have shown that decision to choose different market outlets by smallholder farmers is affected by various characteristics, such as resource endowment, access to a different market outlet, prices, and transport cost **(Jaleta & Gebremedhin, 2012; Kuma *et al.*, 2013; Shewaye, 2016).** In other studies, by **Geoffrey *et al*. (2014)**, farmers' decision on market outlet choice is influenced by several factors: farm size, price attitude, contract arrangement, and distance to market. Lack of market information or challenges in accessing more rewarding markets make smallholder farmers sell their produce through outlets offering low prices.

Even though farmers sell beans through the different market outlets, no empirical studies have been done to determine whether partnerships influence market outlet choice for bean farmers in developing countries. Therefore, this study further investigated the influence of partnership on the selection of market outlets for smallholder bean farmers. In order to alleviate market pressure, the agricultural market is evolving into a vertically coordinated system; thus, a detailed analysis of the relationship between partnership and market can be significant in developing livelihood improving programs in developing countries; this may help find out ways in which market participation among smallholder farmers can be improved.

DATA AND METHODS

The study used a multi-stage sampling technique to select the respondents. In the first stage, Homa Bay County was purposively chosen since it was one of the targeted areas for the pre-cooked bean project. In the second stage, out of 8 sub-counties in Homa Bay County, four sub-counties were purposively selected: Suba North, Homa Bay town, Ndhiwa, and Rangwe; this was because the project was implemented in those sub-counties. In the third stage, a list of farmers that participated in PPP was generated from each of the four sub-counties. In the fourth stage, Systematic random sampling of participants was selected proportionate to the actual size of the participant from each sub-county. In the final stage, to get non-participant simple random sampling was used. In determining factors influencing smallholder bean farmers' choice for the market outlet, the original sample of 362 households was reduced to 253 households in the bean production system; this was due to some of the farmers not selling their beans but instead keeping them for household consumption. Out of 253 farmers, 147 participated in PPP, and 106 were non-participants.

Data collection and analysis

Data was collected through single farm visit interviews using structured questionnaires. The dependent variables, which were market outlet choices, were binary for all the market outlets, indicating a preference for that market outlet and zero otherwise. A binary selection model would appropriately fit the analysis due to the dichotomous nature of the dependent variable **(Deb & Trivedi, 1997; Greene, 2002**). The four-market outlet chosen were brokers, consumers (direct consumers and institutions like schools), retailers, and wholesalers. The primary data that was collected included socioeconomic and institutional characteristics of farmers, outlets used by farmers to sell their beans in the market, the reason for selling to those markets, prices offered by different markets, and income received from the sales of beans. Data collected was coded, recorded, cleaned, and analysed using statistical packages software's (SPSS v25 and STATA v16)

Empirical model

The study adopted Multivariate Probit (MVP) to simultaneously model the influence of a set of explanatory variables on bean farmers' choice of the market outlet. Smallholder farmers are more likely to choose more than one market outlet to maximize sales and reduce the risk of choosing one. Farmers consider asset or bundle of possible channel choices that maximize their expected utility **(Arinloye *et al*., 2012, 2015);** hence selection decision is multivariate and using of univariate model exclude useful economic information contained in interdependent and simultaneous choice decisions **(Dorfman,1996**). Estimating independent binary equations for each market would lead to potential bias because the analysis does not allow correlation of error terms, leading to inefficient estimates. Thus, selection decisions were modeled using the MVP model to account for these shortcomings. The MVP model simultaneously regresses a combination of several correlated binary equations against a single vector of explanatory variables **(Cappellari and Jenkins, 2003; Kassie *et al*., 2013; Teklewold *et al*., 2013)**. To determine the appropriateness of the MVP model for analysis and the relationship between the market outlets, error terms between binary correlation coefficients of the four market outlets equations were estimated.

Farmer choice of bean marketing outlet in an expected utility framework is based on random utility theory **(Green, 2000).** The utility is determined by a set of exogenous variables that influence farmers' market outlet choice. Therefore, the decision of a farmer to sell to a particular market outlet depends on whether that market outlet gives the farmer higher utility than another outlet. The utility of economic agents is not observable, but their action is observed through their choice.

Consider the i^{th} household (i=1…. N), which confronts whether or not to choose available market outlets over the specified time horizon. Let u_j represent the farmer's benefit to select j^{th} market outlet, where j represents the different choice of market outlets (R retailers, W wholesalers, B brokers, C consumers). Equation (1) shows that the farmer decides to choose j^{th} market outlet if

$$y_{ij} = u_j - u_o \geq 0 \tag{1}$$

Equation (2) shows that the net benefit γ_{ij} that farmer i derives from choosing a market outlet as a latent variable determined by observed explanatory variable x_i and disturbance term ε_i .

$$y_{ij} = X_{ij}\,\beta_{ij} + \varepsilon_i \tag{2}$$

Where;

y_{ij} dependent and variable for channel choice of brokers, retailers, wholesalers, and consumers;

X_{ij} the combined effect of the explanatory variable;

β_{ij} vector parameter;

ε_i error term.

with $y_{ij} = 1\; if\; y_{ij} \geq 0\; and\; 0$ if otherwise (3)

In a multivariate model, where the choice of several market outlets is possible, the error terms jointly follow a multivariate normal distribution (MVN) with a mean of zero and variance-covariance matrix and has values of 1 on the leading diagonal, where $(\mu_R, \mu_W, \mu_{B,}\, \mu_C) = MVN \approx 0, \Omega \quad p_{ij}$ represents the correlation off-diagonal elements, the asymmetric covariance matrix is given by (Eq. 4).

$$\Omega = \begin{bmatrix} 1 & PRW & PRB & PRC \\ PWR & 1 & PWB & PWC \\ PBR & PBW & 1 & PBC \\ PCR & PCW & PCB & 1 \end{bmatrix} \tag{4}$$

Equation (4) generates the MVP model that jointly represents a decision to choose a particular market outlet. The diagonal element in the variance-covariance matrix represents the unobserved correlation between the stochastic components of different outlets. The specification with non-zero off-diagonal elements allows for correlation across disturbance terms of several latent equations, representing unobserved characteristics that affect the choice of alternative outlets. Selecting an appropriate market channel is not easy because different factors influence market outlet choices. Household Socio-economic variables, market factors, and institutional factors were used to analyse market outlet choices derived from previous studies **(Arinloye *et al*., 2015; Geoffrey *et al*., 2015; Abera *et al*., 2016; Tarekegn *et al*., 2017).**

RESULTS AND DISCUSSION

This section presents and discusses the study findings. It begins by showing descriptive statistic results of significant categorical variables (Table 1) such as gender, group membership, and partnership in relation to smallholder bean farmers' choice of marketing outlet. Traders play a crucial role in buying beans. Some buy at the farm gate, and some believe at a marketplace. Buyers of beans in the study area included; wholesalers, retailers, brokers, and consumers. Wholesalers comprised 35.44 %, wholesalers buy bean grain mainly from individual farmers, some collectors/small traders, and a few other wholesalers. Retailers were 34.74%; they buy beans from wholesalers and farmers in their surroundings and directly sell to consumers. Consumers who were direct consumers and school comprised 16.14%. Finally, brokers comprised 13.68%; they physically handle products for buyers and sellers and are paid on a commission basis for the services rendered.

The most preferred outlet among female farmers was wholesalers, with 77.23% female selling to the outlet. The least preferred was brokers, with only 61.54% selling to brokers. For male farmers, the most preferred outlet was a broker with 38.46% selling to brokers, and the least preferred was wholesalers, with only 22.77% male farmers selling to the outlet. However, there was a statistical difference at a 5% significance level for male and female farmers that sold their beans to broker outlets. The result shows that the majority of the female farmers were able to participate more in bean farming as compared to their male counterparts, hence the choice of wholesaler market outlets.

There was a significant difference for those farmers who supplied their beans to the wholesaler market. Farmers who supplied their beans to brokers, consumers, retailers, and wholesalers acquired credit from the bank, microfinance, and other informal sources represented 25.64%, 32.61%, 35.35%, and 47.52% respectively.

Education level was broken down into four categories; none, primary, secondary and tertiary. The majority of farmers who sold their beans to different market outlets had primary education. However, there was a significant statistical difference for farmers that sold their beans to broker and wholesaler market outlets.

In regard to training, 51.28%, 71.74%, 58.59%, and 59.41% of farmers that supplied their beans to brokers, consumers, retailers, and wholesalers received training, respectively. However, there was a significant difference for those farmers that supplied their beans to the consumer market. Result confirms that the majority of the farmers in the group sold their beans to the consumer market, which comprised direct consumers and schools. From the finding of this study, 48.72 %, 69.57%, 49.49%, and 67.33% of the farmers in partnership supplied their beans to brokers, consumers, retailers, and wholesaler market outlets, respectively. However, there was a significant difference between farmers who sold their beans to consumer, retailer, and wholesaler market outlets. Results indicate that most farmers who participated in the partnership supplied their beans to consumer and wholesaler market outlets.

Descriptive statistics for the continuous household variables are summarised in Table 2. The results indicate that the minimum age of the bean farmers was 20 while the maximum age was 80 years. The mean age of farmers selling to broker's outlets was 42.6, while consumers, retailers, and wholesalers were 46.4, 44.3, and 46.3, respectively. However, there was a minimal difference for farmers who sold their beans to the broker market. This indicates that farmers who sold their beans to broker outlets were slightly younger than those who sold to other outlets. This may be attributed to the fact that younger people do not take time in search of a better market as compared to older people.

In terms of experience in bean farming, results indicated that the minimum number of years for bean farming was one while the maximum year of experience in farming was 40. This implies that there were farmers with little and others with more experience in bean farming. The mean years in bean farming experience was 8 for brokers and consumers, 10, 9 for retailers, and wholesalers, respectively; however, there was a statistical difference in bean farming experience for those farmers that sold their beans to retailers. Experienced farmers have a better knowledge of the cost and benefits of various bean marketing outlets, thus leading to informed choices on the market with better returns, such as the retailer market.

The minimum land size was 0.1 hectares, while the maximum was 3.6 hectares. The mean land size under bean production was less than one hectare across the market outlets, with 0.5, 0.6, 0.4, and 0.7 hectares for farmers who sold their beans to brokers, consumers, retailers, and wholesalers. However, there was a high statistical difference between those farmers that sold their beans to retailers and wholesalers' markets. Land size is an important asset that affects marketable surplus. Result confirms that farmers with big land sizes were able to participate more in bean farming and thus choose a wholesaler market outlet.

Regarding distance, the mean distance transported in kilometers was 1.8, 0.4, 2.5, and 2.4 for brokers, consumers, retailers, and wholesalers, respectively; however, there was a high statistical difference for those farmers who sold their beans to retailers and wholesalers' markets. The minimum number of visits by extension service provider was 0, and the maximum was five times within the last year. Extension services are a means of disseminating production and marketing information to farmers and consequently affecting their output. The mean number of extension services received was 0.9, 0.8,1, and 1.2 for farmers who sold their beans to brokers, consumers, retailers, and wholesaler market outlets. Nevertheless, there was a high statistical difference for those farmers who sold their beans to the wholesaler's market.

Table 3 shows the differences between participants and non-participants of PPP. The result shows that there was a statistical difference between the two groups. The mean quantity harvested was 3.3 for PPP participants, whereas for non-participants were 2.9; the difference was significant at a 1% significant level. The mean price for PPP participants was 139, whereas for non-participants were 135 the difference was significant at a 10% significance level.

Table 1: Descriptive statistics for categorical variables

Categorical variable	Brokers (*n*=39)		Consumers (*n*=46)		Retailers (*n*=99)		Wholesalers (*n*=101)	
	%	pr	%	pr	%	pr	%	pr
Sex								
Female	61.54	0.047**	69.57	0.416	74.75	0.898	77.23	0.386
Male	38.46		30.43		25.25		22.77	
Level of education								
none	10.26	0.079*	10.87	0.873	10.1	0.873	11.88	0.028**
primary	43.59		56.52		56.57		69.31	
secondary	38.46		28.26		28.28		14.85	
tertiary	7.69		4.35		5.05		3.96	
Non-farm income								
yes	64.1	0.144	54.35	0.882	56.57	0.412	48.51	0.208
no	35.9		45.65		43.43		51.49	
Acquire credit								
yes	25.64	0.106	32.61	0.481	35.35	0.635	47.52	0.005***
no	74.36		67.39		64.65		52.48	
Received training								
yes	51.28	0.294	71.74	0.050**	58.59	0.936	59.41	0.893
no	48.72		28.26		1.41		40.59	
Group Membership								
yes	64.1	0.697	76.09	0.139	65.66	0.757	68.32	0.676
no	35.9		23.91		34.34		31.68	
Partnership								
yes	48.72	0.197	69.57	0.082*	49.49	0.026**	67.33 |	0.015**
no	51.28		30.43		50.51		32.67	

Table 2: Descriptive statistics for continuous variables

	Brokers Mean Std. Dev	t-test	Consumers Mean Std. Dev	t-test	Retailers Mean Std. Dev	t-test	Wholesalers Mean Std. Dev	t-test
Age	42.641 (13.39)	0.0919*	46.413 (14.57)	0.674	44.374 (15.027)	0.302	46.277 (14.493)	0.542
Experience in bean farming	8.410 (7.563)	0.372	8.043 (6.730)	0.1852	10.101 (9.046)	0.0263**	9.069 (6.977)	0.257
price	139.28 (23.65)	0.000***	135.04 (26.37)	0.000***	140.13 (27.2)	0.000**	137.712 (27.736)	0.000***
Total land in hectares	0.858 (0.598)	0.682	0.869 (0.572)	0.546	0.730 (0.471)	0.0381**	0.898 (0.672)	0.089*
Land under bean production in hectares	0.495 (0.468)	0.334	0.591 (0.424)	0.776	0.418 (0.362)	0.0005***	0.729 (0.656)	0.0003***
Number of visits by extension	0.900 (0.706)	0.691	0.828 (0.785)	0.271	1.039 (0.708)	0.334	1.197 (0.831)	0.005***
Distance to market	1.831 (1.599)	0.189	0.4601 (2.155)	0.444	2.561 (1.845)	0.0000***	2.429 (2.428)	0.0000
Quantity harvested	3.946 (1.044)	0.008	3.400 (1.208)	0.663	3.585 (1.208)	0.228	3.459 (1.239)	0.899

Table 3: Continuous variables comparison for PPP participants and non-participants

	Public- private partnerships participants		Non-participants		
	Mean	Std. Dev.	Mean	Std. Dev.	t test
log of quantity harvested	3.316	1.275	2.867	1.220	0.001
Price	139.624	22.101	135.025	23.539	0.058
Land under bean production	0.703	0.601	0.413	0.395	0.000

Table 4: Categorical variables comparison for PPP participants and non-participants

	Public- private partnerships participants %	Non-participants %	pr
Receive extension service			0.000***
YES	87.07	17.92	
NO	12.93	82.08	
Receive training			
yes	89.8	16.04	0.000***
NO	10.2	83.96	
Group membership			
Yes	85.03	41.51	0.000***
NO	14.97	58.49	0.000***
Acquire credit			
yes	51.7	16.98	0.000***
No	48.3	83.02	

PPP participants allocated more land than non-participants; the mean land allocated for bean production was 0.7 for PPP participants, whereas for non-participants were 0.4, the difference was significant at a 1% level.

Table 4 presents institutional factors for comparison between PPP participants and non-participants. From the result, the majority of the farmers that participated in PPP received extension services, training, and credit and were group members. Chi-square value was significant at 1% significant level across all variables; this means that there was a significant difference between the two groups.

The Wald test indicated that the MVP was fit for analysis. The null hypothesis that the market outlets' choice decision for the four-market outlets being independent was rejected at a 1 % significance level. The likelihood ratio test in the model indicated that the interdependence between market outlet choices decision was rejected at a 1 % significance level and that there are joint correlations for four estimated coefficients across the equations in the model. This verifies that separate estimation of choice decision to choose the four-market outlet choice for the beans is interdependent for household decision. This suggests that the Multivariate Probit model had strong explanatory power and hence the model fits the data reasonably, the result for MVP is presented in Table 5.

The farmer's age had a negative and significant influence on the choice of broker outlet at a 95% confidence level. This means that a one-year increase in the farmer's age reduces the likelihood of the household delivering to brokers by 18%. This suggests that the older the household head becomes, the less the likelihood of delivering their beans to the broker's market. This might be because older people might have marketing experience, accumulated capital, or a long-term relationship with their clients or might have preferential access to credit due to their age and availability of land. The result also confirmed that older farmers choose a better market outlet than young farmers. The aged people are more conventional, avoid market participation through intermediaries, and prefer direct participation. Older people avoid exploitation by brokers since they play the role of intermediary. This study concurred with the finding of **Anteneh *et al*. (2011),** who found out that there was a negative relationship between age and the proportion of coffee sold to cooperatives by non-members.

Experience in bean farming had a negative and significant influence on the choice of wholesaler market outlets. A one-year increase in bean farming experience decreases the likelihood of bean farmers by 21 % to sell to a wholesaler market. This result indicated that more experienced households in bean production were less likely to deliver beans to wholesaler market outlets than less experienced farmers. Experienced farmers have a better knowledge of the cost and benefits associated with various bean marketing outlets; consequently, they are more likely to decrease the quantities supplied through the wholesaler market outlet and increase the amount supplied to other lucrative market outlets. The negative relationship between experience in bean farming and selling to wholesaler outlets can be explained by the fact that experienced farmers can make informed decisions concerning the choice of marketing outlets to sell their farm produce based on the marketing margin and marketing cost involved, such as logistic. According to **Shiimi *et al.* (2012),** experience replicates the ability of the seller to negotiate marketing transactions to their benefit better.

Non/off-farm income negatively affects the probability of choosing a wholesaler market outlet at 5% levels of significance. This indicates that bean farmers involved in non/off-farm activities are less likely to sell their produce to the wholesaler market than those who do not have non-farm income. Moreover, farmers involved in off/non-farm activities are less likely to sell their beans to retailers, consumers, and broker outlets than farmers who don't have non-farm income. The possible explanation is that farmers involved in non/off-farm activities have less time to spare to produce marketable surplus; hence, this decreases the probability of participating in the wholesaler market channel, which is a larger market than other markets. Non-farm income gives farmers an extra source of income, and therefore, they do not have to be concerned about producing more for the wholesaler market. The rationale is that they produce beans production for consumption, and when they get surplus, they sell to other markets.

This study revealed that, as the land size allocated for bean production increases by 1 hectare, the probability of farmers selling their produce to the retail outlet decreases by 98 %, whereas the probability increases by 58% to sell to the wholesaler market outlet ceteris paribus. This indicates that those households who allocated large size of land for bean production would produce more output, and farmers would be more likely to sell their produce to the wholesaler market outlet and less likely to sell their produce to the retailer market outlet. This means that farmers receive higher prices from the wholesale market outlet than retailer market outlets from the sale of bean products. The result of this study is also consistent with **Takele *et al*. (2017),** who found out that the probability of selling to wholesalers increased as the number of mangos produced increased.

Price had a negative and significant influence on consumers' market outlet choice at a 95% confidence level. This means that a one-unit increase in price reduces the likelihood of farmers selling their beans to the consumer market. The possible reason may be that other farmers and institutions (schools) consumers offered lower prices than other outlets. Upon probing why they would sell to consumers, i.e., institutions and direct consumers, most farmers said they agreed that they would take their beans to schools, and the earnings would be used to offset their children's school fees. Farmers will avoid the lowest paying outlet (consumer) and go for one that pays better. Pricing plays a vital role when farmers make decisions on the choice of market outlet to sell their products. **Mburu *et al*. (2007)** found that more farmers in central Kenya chose the higher milk price channel. **Staal *et al*. (2006)** also found a positive relationship between the price offered for milk and Marketing channel choice in Gujarat. Higher prices increase farmers' margins and act as motivation to produce more and get more income.

Distance to the market had a significant and negative influence on the choice of broker market outlet by 11%. This means that one increase in one kilometer's distance negatively influenced the choice of broker market outlet. An increase in one kilometer will result in farmers selling to consumer, retailer, and wholesaler markets. Smallholder farmers decide between selling at the farm gate and receiving a low price or traveling to the market where you can receive a better price but incur transaction costs. Brokers usually buy at the farm gate, but farmers avoid them due to them offering low prices.

This study revealed that engagement in the partnership had a positive and significant influence in selling to wholesaler markets. The possible reason may be that most of the farmers in partnership received farm input for free and others on credit, increasing the level of their participation in bean farming compared to those that did not engage in a partnership. The partnership had a positive impact on bean output, and as a result, farmers increased the amount of bean harvested hence the choice of wholesaler market outlet. Wholesaler becomes the best option when you have more quantity since they will carry all your supply, unlike retailers you have to sell to several.

Access to credit was positively related to the probability of choosing a wholesaler market outlet, and credit access increased the choice probability by 40 percent, *ceteris paribus*. Access to credit increases access to resources needed for production. Covering transport costs to the market allows farmers to purchase inputs such as seed and fertilizer, increasing production, leading to a marketable surplus. This result concurred with **Tura & Efa (2018),** who found that credit access had a positive and significant effect on retailers' market outlets. Access to credit increases an individual's access to resources needed to cater to production and marketing costs. **Randela *et al.* (2008)** found that credit availability allows farmers to meet transaction costs of output and input markets in South Africa. Therefore, the positive relationship between credit access and the choice of wholesale outlets means that farmers who have access to credit can meet the production and marketing costs in the wholesaler marketing channel. Access to training had a positive and significant influence in choosing the retailer market. The results of this study indicated that access to bean production training increases the household likelihood of selling its beans to the retailer by 41 % at a 95% confidence level. The results imply that it is likely that the training received by the bean farmers selling to retailer outlets impacted their high probability of selling beans to the outlets. Farmers who were probed on the accessibility of training received reported that most extension officers regularly organize training and are available at any given time. However, it is argued that farmers with higher education levels may have a superior ability to access and understand more information and technology. Therefore, applying that knowledge to venture into new opportunities than farmers with lower education **(Nyaupane & Gillespie, 2010)**.

CONCLUSIONS AND RECOMMENDATIONS

This paper investigated factors influencing the choice of market outlets by bean farmers using multivariate probit. Identifying factors influencing bean farmers' choice of market outlets is significant for developing the bean value chain. Experience in bean farming, farm size, access to training, credit, and partnership participation positively and significantly influenced selling to this market. The majority of the farmers who participated in PPP sold their beans to wholesaler market outlets. The study's findings showed a significant difference in quantity harvested and price received from the sale of beans for PPP participants and non-participants. Farmers who participated in partnership received farm input for free and others on credit, increasing their participation level in bean farming compared to those who did not engage in a partnership. Therefore, a wholesaler becomes the best option when you have more quantity since they will carry all your supplies, unlike the other outlets.

Based on the findings of this study, PPP could be an effective way of improving smallholder livelihood; policies that include reduction of cost to smallholder farmers such as more significant tax incentives for farm inputs, subsidized farm inputs, and credit could significantly improve farmers' income. Alternatively, policies that include mechanisms that create or secure markets for smallholder farmers will see that they get increased returns.

Table 5: Multivariate Probit result for factors influencing the choice of market outlets

	Brokers (*n*=39)			Consumers (*n*=46)			retailers (*n*=99)			Wholesalers (*n*=101)		
	Coef.	Std. Err	P>z	Coef.	Std. Err	P>z	Coef.	Std. Err	P>z	Coef.	Std. Err	P>z
Age	-0.018	0.009	0.037**	0.002	0.008	0.811	-0.011	0.007	0.104	0.002	0.006	0.739
Sex	0.338	0.245	0.169	0.217	0.241	0.368	0.056	0.213	0.793	-0.069	0.199	0.727
Years of schooling	-0.004	0.031	0.894	0.008	0.030	0.781	0.009	0.025	0.728	-0.037	0.024	0.116
Experience in bean farming	0.000	0.017	0.98	-0.023	0.016	0.165	0.019	0.013	0.153	-0.021	0.012	0.086*
Non-farm income	0.099	0.219	0.652	0.007	0.204	0.972	0.104	0.178	0.559	-0.314	0.167	0.061*
Total land in hectares	0.408	0.313	0.193	0.161	0.298	0.588	0.262	0.262	0.318	-0.214	0.255	0.403
land under bean Production in hectares	-0.455	0.319	0.154	-0.248	0.297	0.405	-0.989	0.297	0.001***	0.567	0.267	0.033**
Price/kg	-0.003	0.003	0.354	-0.005	0.003	0.093*	0.002	0.003	0.544	-0.001	0.002	0.801
Quantity harvested	0.104	0.086	0.224	-0.102	0.081	0.205	0.003	0.070	0.965	0.054	0.068	0.428
Group membership	-0.005	0.284	0.985	0.152	0.270	0.574	-0.049	0.241	0.839	-0.189	0.234	0.42
Distance transported (kms)	-0.115	0.066	0.082*	-0.077	0.053	0.15	0.033	0.040	0.415	0.034	0.042	0.416
Extension contacts	-0.001	0.295	0.997	0.273	0.297	0.358	0.127	0.271	0.641	-0.410	0.259	0.114
Engage in partnership	-0.182	0.315	0.563	0.089	0.318	0.779	-0.737	0.302	0.015**	0.825	0.268	0.002*
Access to credit	-0.239	0.255	0.349	-0.315	0.238	0.185	0.030	0.208	0.884	0.395	0.196	0.044**
Received training	0.074	0.313	0.812	0.170	0.344	0.621	0.636	0.311	0.041**	-0.337	0.283	0.234

Note ***1% **5%   *1% significance level

Further research needs to be done focusing on different value chains to understand better the overall effect of PPP performance and how effective PPP can be used in the marketing of different products in the agricultural value chain. Most rural households in Africa don't keep farm records, and capturing accurate data was a challenge since we relied on recall to gather information on the marketing of beans; however, to overcome this challenge, the study covered a recent period for ease of recall. Further research needs to be done focusing on different value chains to understand better the overall effect of PPP performance and how effective PPP can be used in the marketing of different products in the agricultural value chain.

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TWO-STAGE DEA ESTIMATION OF TECHNICAL EFFICIENCY: COMPARISON OF DIFFERENT ESTIMATORS

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ABSTRACT

Research background: The challenge of resource limitations requires that farmers make judicious use of resources to maximize output and profit levels. This can be achieved through assessment of resource-use efficiency of farmers by estimating the level of technical efficiency and the determining factors.
Purpose of the article: This paper compared the results of alternate DEA methodologies and applied different estimators to measure the influence of exogenous factors on technical efficiency of groundnut farmers in northern Ghana.
Methods: The study used the traditional and double bootstrap DEA approaches to estimate technical efficiency while in the second stage, OLS, Tobit and double bootstrap techniques were used to estimate the influence of exogenous factors on efficiency.
Findings & Value added: The double bootstrap DEA approach produced a mean technical efficiency of 51 per cent compared to 70 per cent for the traditional DEA approach. Concerning the determinants of technical efficiency, the DEA with Tobit (DEA+Tobit), DEA with OLS (DEA+OLS), and Simar and Wilson's double bootstrap DEA (SW-DEA) procedures produced very similar results. The findings shed light on two-stage DEA estimation as well as the modelling of the influence of exogenous factors on the DEA scores.

Keywords: Technical efficiency; two-stage DEA; double bootstrap; OLS; Tobit model
JEL Codes: C21; D24; Q12

INTRODUCTION

Technical efficiency (TE) analysis is a major field in empirical economics with wide application in other fields of study. Efficiency estimation in agriculture has gained considerable attention in the economic literature due to resource limitations of farmers and the need to make judicious use of resources to maximize output and profit levels, or any other economic objective of the producer. Agricultural production in most developing countries is predominantly a small-scale activity. Smallholder production is typically characterised by dependence on rainfall and little application of productivity-enhancing technologies such as modern seeds, irrigation technology and mechanisation (**Diao, 2010; Chamberlin, 2007; ISSER, 2006**). Coupled with other constraints such as inaccessibility to agricultural support services and basic infrastructure like road networks and markets, productivity of smallholder agriculture has been rather low, which is a concern to policymakers and the research community. Critical to the low productivity of smallholders is the presence of inefficiency in production due to sub-optimal allocation of resources and inadequate management skills. In order to increase the productivity of smallholder producers, measures are required to enhance TE of production, especially the technical aspects of production.

Efficiency analysis is typically classified into parametric approach using stochastic frontier analysis (SFA) and nonparametric approach using data envelopment analysis (DEA). The SFA has its appeal in the fact that it provides a measure of both the estimate of efficiency and its determinants. In other words, SFA directly provides a measure of the sources of inefficiency, which in many empirical studies are of much more importance to policy-making than the mere estimation of the level of efficiency of individual production units. The DEA methodology, however, measures the input-output combinations that yield maximum output without directly addressing the factors explaining the differences in efficiency between the best performing decision-making units (DMUs) and their less efficient peers.

In the light of this limitation with the nonparametric approach, semi-parametric two-stage DEA approaches that combine regression analysis with the nonparametric DEA efficiency estimation have gained popularity and extensive application in recent years. Typically, researchers rely on either a Tobit model (because of the bounded nature of the DEA estimates) or ordinary least squares (OLS) for the second stage estimation (**Hoff, 2007; McDonald, 2009; Simar & Wilson, 2011**). These two-stage estimators have been widely used in the efficiency literature mainly for their intuitive appeal. Other methodologies for non/semi-parametric efficiency estimation can be found in the literature. This study, however, focuses on three of the commonly used approaches and compares the efficiency outcomes by applying these estimators to a dataset generated from smallholder producers in Ghana.

While DEA estimation of TE is widespread, the method has not been without some criticisms which include the absence of a clear data generation process (DGP) and the presence of serial correlations between the estimated DEA scores (see **Simar & Wilson, 2007; McDonald, 2009**). The latter problem arises mainly because the DEA procedure is derived from a common sample. The estimation of each firm's TE uses information on the whole sample; hence the estimated scores are considered to suffer from serial correlation.

Simar & Wilson (2007) advocated a parametric technique to solve the above-mentioned problems with the two-stage DEA estimation. Instead of a censored regression model, they proposed truncated regression with bootstrapping to provide a data generation process that mimics the true process. With the double bootstrap methodology, double bootstrapping is performed on the efficiency scores to eliminate unknown serial correlations associated with the initial DEA scores. The stage two analysis involves truncated regression to regress the first-stage bootstrap DEA scores on environmental variables expected to affect efficiency. Recent applications of the double bootstrap technique in empirical studies include **Nkegbe (2018), Fragkiadakis *et al.* (2016), Urdiales *et al.* (2016)** and **Chortareas *et al.* (2013)**. The traditional DEA approach does not include a bootstrapping procedure, but applies a second stage estimation whereby the predicted DEA scores are regressed on environmental factors assumed to influence efficiency, using either an ordinary least squares regression (so-called DEA+OLS model) or Tobit regression (so-called DEA+Tobit model). Advocates for the traditional DEA approach followed by ordinary least squares regression (DEA+OLS approach) include **Banker *et al.* (2019)** while authors who have used the Tobit model for the second stage analysis in the extant literature include **Abdulai *et al.* (2018), You and Zhang (2016)** and **Kutlar *et al*. (2013)**.

However, the Simar and Wilson (SW) approach is not without its own criticisms. For example, the SW approach completely ignores random noise, which is an important factor in estimating efficiency. SW's double bootstrap technique corrects twice for bootstrap bias to give an approximation of the true or population DEA score. The supposition that the bootstrap bias is an approximation of the model or DEA bias has been challenged by **Tziogkidis (2012)**. **Banker & Natarajan (2008)** prescribed sufficient conditions for the OLS estimator to yield consistent estimates of the influence of contextual (environmental) variables in two-stage DEA analysis. In a recent study, **Banker et al. (2019)** demonstrated from Monte-Carlo simulations that the simple DEA+OLS approach performs better than the more complicated SW approach. **Hoff (2007)** compared different approaches for two-stage DEA modelling and observed that the Tobit model was sufficient in modelling the second stage DEA model. The author further observed that OLS was in many cases a sufficient replacement for the Tobit model in the second stage DEA estimation. **Johnson & Kuosmanen (2012)** also developed a one-stage DEA approach which they found to outperform the DEA+OLS. The authors showed that the two-stage DEA estimator is statistically consistent under more general conditions, adding that the finite sample bias of DEA in stage one is carried across to the stage two analysis resulting in biased estimates of the contextual variables.

The paper compares two-stage DEA estimation using SW double bootstrap approach (with truncated regression) and the traditional DEA approach with OLS and Tobit regression through a case study in the Ghanaian farm sector. The paper compares three approaches (estimators) for estimating the influence of exogenous factors on DEA scores, in order to determine whether these estimators yield comparable estimates. The paper's departure from previous studies is that it applies real data to test the results from using these estimators. Even though comparison of alternative estimators exists in the literature (**Banker *et al*., 2019**), studies using real data set instead of Monte Carlos simulations are rare. Hence, this study attempts to fill that void by providing analysis based on real data set.

RESEARCH METHODOLOGY

The study area and sampling procedure

The data for the analysis came from 158 smallholder groundnut cultivators in the Tolon district which is situated in the northern savanna of Ghana. The district has a single rainfall regime with high daily and night temperatures. Groundnut production is an essential income-generating activity in the district, which is agrarian. Farmers were sampled from eight communities in the district which were selected based on groundnut production potential. Twenty farmers were sampled from each community. Data were collected on production, socio-economic and institutional factors through questionnaire administration. After the data entry and cleaning, two respondents were dropped due to incomplete information on their farming activities.

Data envelopment analysis

DEA model can be formulated as a minimisation objective function applying linear programming. The DEA model compares the efficiency of each DMU to a constructed efficiency frontier. Shortfalls in production from the efficient frontier are reported as inefficiency. DEA is estimated under constant returns to scale (CRS) or variable returns to scale (VRS) assumptions. The CRS (**Charnes *et al*., 1978**) assumes that all the DMUs are operating at an optimum scale, a condition which is relaxed in the case of VRS proposed by **Banker *et al.* (1984)**. DEA estimation also follows either an input or output orientation, depending on which factors farmers have much control over. Smallholders have greater control over factors of production than outputs hence an input approach is generally preferred. For CRS, the DEA procedure is presented as follows (**Coelli *et al*., 2005**):

$$
\begin{aligned}
&min_{(\theta,\lambda)}\ \theta \\
&\text{s.t.} \quad -q_i + Q\lambda \geq 0 \\
&\qquad\ \ \theta x_i - X\lambda \geq 0 \qquad\qquad (1)\\
&\qquad\ \ \lambda \geq 0
\end{aligned}
$$

where θ is the estimate of efficiency taking values between zero and one, q is output, Q denotes an output matrix, x denotes inputs, X denotes an input matrix and λ represents weights. Efficient farms have θ of one while any deviation from this value indicates inefficiency.

Including the convexity constrain, $N1'\lambda = 1$ gives the DEA model under VRS.

$$
\begin{aligned}
&min_{(\theta,\lambda)}\ \theta \\
&\text{s.t.} \quad -q_i + Q\lambda \geq 0 \\
&\qquad\ \ \theta x_i - X\lambda \geq 0 \qquad\qquad (2)\\
&\qquad\ \ N1'\lambda = 1 \\
&\qquad\ \ \lambda \geq 0
\end{aligned}
$$

where $N1$ denotes a vector of ones. θ in equation 2 gives an indication of pure technical efficiency while the corresponding value in equation 1 gives total efficiency, which comprises scale efficiency (SE) and pure TE. SE is derived as the ratio of the value of θ under CRS assumption to that under VRS, that is $SE = \theta_{CRS}/\theta_{VRS}$.

Second-stage DEA analysis

The effect of exogenous variables in DEA estimation has gained attention in the extant literature. Of particular interest is the choice of estimator for the second stage analysis. Unlike SFA where efficiency and its determinants are estimated simultaneously in a single step, DEA typically relies on externally generated DEA scores which are regressed on exogenous variables to evaluate the drivers of inefficiency. According to the existing literature, the dominant approaches for estimating the second stage regression analysis in DEA studies include OLS (DEA+OLS), Tobit regression (DEA+Tobit) as well as Simar and Wilson double bootstrapping technique (SW). Other approaches like the order-m approach (**Cazals *et al.*, 2002**) and one-stage DEA (1-DEA) proposed by **Johnson & Kuosmanen (2012)** have been considered in the literature. With DEA+OLS, the efficiency scores are regarded as continuous variables and the OLS estimator is deemed suitable for analysing the effect of exogenous variables. Advocates for the OLS as appropriate estimator for the second-stage DEA analysis include **Banker *et al.* (2019)** who argue that the DEA+OLS outperforms the DEA+Tobit, and **Banker & Natarajan (2008)** who prescribe conditions that make the application of OLS in the second stage to give consistent estimates of the effect of environmental variables. The DEA+Tobit, on its part, derives its appeal from the fact that the DEA scores exhibit the characteristics of censored data. Several authors have used this approach in DEA studies in the existing literature (**Dassa *et al.*, 2019; Abdulai *et al.*, 2018; Akpalu *et al.*, 2012**).

The SW double bootstrap approach considers the lack of a coherent DGP in the estimation of DEA as a limitation. The proponents of the double bootstrap approach contend that the DEA scores are estimated in a way that utilizes information on all the individuals in the sample, resulting in efficiency estimates that are serially correlated. What the bootstrapping technique seeks to achieve is to produce a DGP that mimics the true DGP using bootstrapping technique to correct for the serial correlations associated with the DEA scores. Artificial efficiency scores are computed by simulation from which bootstrapped coefficients and standard errors are produced. Confidence intervals are generated using the bootstrap results. In the second stage, further bootstrapping is carried out to generate new confidence intervals for the estimation. The SW approach uses truncated regression in the second stage estimation. A complete description of the double bootstrap technique is contained in **Simar & Wilson (1998, 2000, 2007)** and **Nkegbe (2018)**.

The regression equation estimated in the second stage was expressed as:

$$\hat{\theta}_i = \beta_0 + Z_i\beta + \varepsilon_i \qquad (3)$$

where $\hat{\theta}$ is the calculated DEA score, Z is a vector of regressors, and β represents unknown coefficients.

The empirical model of the second-stage regression (truncated, OLS and Tobit) was specified as follows:

$$\hat{\theta}_i = \beta_0 + \sum_{n=1}^{11} \beta_n Z_{ni} + \varepsilon_i \qquad (4)$$

Exogenous factors included in the model were chosen relying on a priori expectation and the existing literature. Gender influences TE of smallholders due to differences in access to and ownership of production resources (**Anang *et al.*, 2016**). Also, age influences TE of production according to the extant literature. Younger farmers may be more adventurous and more likely to take up new innovations in sync with the observation of **Onumah *et al.* (2010) and Shaheen *et al.* (2011)**. In addition, experienced farmers are expected to be more efficient as a result of several years of learning and practicing. Education improves human capital and is associated with higher efficiency of production. Household size can positively influence TE by reducing the likelihood of labour shortage for critical farm operations, which agrees with **Rahman *et al.* (2012)**. Institutional variables like access to credit, farmer group membership, and access to agricultural extension are projected to improve TE (**Asante *et al.*, 2018; Anang *et al.*, 2017**) while partaking in off-farm employment is anticipated to have an indeterminate effect. Where participation in off-farm work leads to reduction in liquidity constraints of the farmers and hence higher capability to afford farm inputs, TE is expected to increase. However, if off-farm activity leads to withdrawal of labour from the farm, then TE is expected to decline. In the case of pests and diseases, higher incidence is expected to increase input use while reducing output level thereby decreasing TE of farmers.

RESULTS AND DISCUSSION

Summary statistics of the sample

Majority of the producers were male farmers with a mean farm and household size of 1.7 hectares and 13 members respectively (Table 1). The result compares with **Danso-Abbeam *et al.* (2015)**, who reported that groundnut cultivators in the Northern region of Ghana had farm size of 1.12 hectares and 12 household members. The age of a typical groundnut farmer was 37 years, with 20 years of farming experience. As indicated by **Danso-Abbeam *et al.* (2015)**, groundnut farmers in the Northern region of Ghana had a mean age of 35.5 years. The respondents also had low level of education which could have a negative impact on farm performance because education has been shown to enhance the quality of human capital and ability to make informed decisions. The low educational level of Ghanaian farmers has been reported by other authors (**Danso-Abbeam *et al.*, 2015; Anang *et al.*, 2016; Anang *et al.*, 2017**).

Also, 38 per cent of the sample took part in off-farm work as supplementary income source while 22 per cent had access to credit. As indicated by **Anang *et al.* (2016)**, 40.3 per cent of rice farmers in northern Ghana had access to agricultural credit. The respondents used little capital input in production while contact with extension agents was low, averaging two contacts for the cropping season. Low access to agricultural extension by farmers in northern Ghana has been highlighted by **Danso-Abbeam *et al.* (2015)**. In addition, only 11 per cent of the sample participated in a farmer group, which in recent times has gained prominence as conduit for extension delivery to smallholders and access to information and production inputs by smallholders. Half of the respondents experienced pest and disease infestation during the cropping season, implying a likely loss of farm output or the use of additional chemical inputs for crop protection.

Technical efficiency analysis

The results of the traditional and double bootstrap DEA efficiency analyses are indicated in Table 2. The double bootstrap approach produced a bias-corrected mean TE of 51 per cent compared to 70 per cent for the traditional DEA. No studies were found that used the double bootstrap approach to estimate technical efficiency of groundnut farmers in Ghana, hence the inability to compare this result with similar studies. **Abdulai *et al.* (2011)** however recorded a mean TE of 70 per cent for groundnut producers in northern Ghana, but their study used SFA. In other studies, **Chakuri (2018)** obtained a TE of 70.5 per cent for groundnut farmers in Ghana (using a Bayesian approach) while **Danso-Abbeam *et al.* (2015)** reported a relatively higher value of 84 per cent (using SFA).

The traditional DEA approach produced TE scores ranging between 0.35 and 1, compared to a range of 0.19 to 0.51 for the bootstrap DEA approach. Also, fewer farmers had very low efficiencies (less than 40 per cent) under the traditional DEA analysis whereas fewer farmers had very high efficiencies (above 90 per cent) for the bootstrap DEA approach. The traditional approach identifies a large proportion of farmers (>33 per cent) as highly efficient (0.81-1.00) whereas the bootstrap approach only finds that 9.5 per cent of farmers are highly efficient. The result is attributed to the sensitivity of the DEA approach to outliers which tends to flatten the efficiency estimates to maximum (**Førsund & Sarafoglou, 2005**). The DEA approach, unlike the stochastic frontier approach, does not handle noise, and tends to treat data with noise as containing outliers, resulting in flattening of the DEA scores towards maximum. The application of bootstrapping technique, however, addresses this sensitivity and produces DEA scores that are relatively lower in magnitude.

The implication of the result is that when estimating TE using DEA, researchers need to take into account the influence of the sensitivity of the DEA approach to outliers on the efficiency scores. The traditional approach overestimates the DEA scores, ostensibly due to the noise in most real data sets. Since most real data sets contain some element of noise, the traditional DEA approach is most likely to overestimate the DEA scores. The use of the bootstrap technique will provide more conservative results without the influence of the sensitivity to outliers.

Determinants of technical efficiency: effects of exogenous variables

In many empirical efficiency analyses, the determinants of efficiency assume a higher importance than the estimated efficiency scores due to the policy implications of the sources of inefficiency. Consequently, identifying the factors associated with (in)efficiency has become an integral part of efficiency analysis. The factors determining TE are indicated in Table 3. **Farrell's (1957)** input-oriented TE measure was used rather than **Shephard's (1970)** output distance function, a reciprocal of Farrell's approach. Hence, the signs of the coefficients are not reversed as in traditional stochastic frontier analysis.

The core question was whether the three estimators – OLS, Tobit and truncated regression models – provide similar results for the 2-stage DEA estimation. The results show that the three estimators provide quite similar results for the second stage regression; although the first stage efficiency scores differ. The signs of the coefficients are quite similar, except the degree to which some of the variables are significant in their effect on efficiency. The bootstrap DEA approach returned a significant value for credit access (albeit at 10 per cent) while the rest of the estimators posted a non-significant value. Also, the OLS estimator posted a non-significant value for household size while both the bootstrap and Tobit estimators returned a significant value at 10 per cent.

The results indicate that women groundnut producers were more technically efficient than their male counterparts. Usually, women are considered to have lower efficiency because of their multiple roles in the household and imbalance in intra-household resource allocation (**Anang *et al.*, 2016; Abdulai *et al.*, 2013**) which affect their farm performance. Female farmers, however, have the potential to be technically efficient in production, when provided with the required production inputs. Thus, the result of the study reiterates women's potential to be technical efficient in production.

Table 1 Descriptive statistics of the sample

Variable	Mean	Std. Dev.	Min.	Max.
Input and output variables				
Output (kg)	1309	882.6	100	4000
Farm size (ha)	1.698	0.854	0.4	4.1
Labour (man-days)	108.1	90.33	20	589
Quantity of seed (kg)	86.22	55.61	14.4	254.4
Cost of ploughing (Ghana cedi)	254.9	128.1	60	600
Simple farm tools (Ghana cedi)	54.34	35.88	10	200
Individual/household characteristics				
Sex (=1 if male)	0.848	0.360	0	1
Age (years)	36.82	11.36	18	70
Years of education	1.070	2.867	0	12
Farming experience (years)	19.51	10.32	2	50
Household size (number)	12.57	6.670	3	40
Institutional variables				
Farmer group (=1 if member)	0.114	0.319	0	1
Extension contacts	2.291	3.779	0	15
Access to credit (= 1 if credit accessed)	0.215	0.412	0	1
Off-farm employment (= 1 if participant)	0.380	0.487	0	1
Farm-specific variable				
Pest and diseases (=1 if infestation occurred)	0.513	0.501	0	1

Source: Author's calculation

Table 2 Distribution of initial and double bootstrap DEA technical efficiency scores

Efficiency range	Traditional DEA score		Double bootstrap DEA score	
	Frequency	Percent	Frequency	Percent
0.11 – 0.20	0	0	3	1.9
0.21 – 0.30	0	0	8	5.1
0.31 – 0.40	10	6.3	45	28.5
0.41 – 0.50	22	13.9	31	19.6
0.51 – 0.60	31	19.6	21	13.3
0.61 – 0.70	27	17.1	26	16.5
0.71 – 0.80	15	9.5	9	5.7
0.81 – 0.90	10	6.3	15	9.5
0.91 – 1.00	43	27.2	0	0
Total	158	100	158	100
Mean	0.70		0.51	
Minimum	0.35		0.19	
Maximum	1.00		0.85	

Source: Author's calculation

Table 3 Determinants of technical efficiency

Variable	Double bootstrap DEA		Traditional DEA + OLS		Traditional DEA + Tobit	
	Coefficient	S. E.	Coefficient	S. E.	Coefficient	S. E.
Sex	-0.1153***	0.0310	-0.0929*	0.0555	-0.1454**	0.0700
Age	0.0012	0.0016	0.0030	0.0029	0.0047	0.0036
Years of education	-0.0048	0.0033	-0.0052	0.0059	-0.0072	0.0071
Experience	-0.0070**	0.0030	-0.0146***	0.0053	-0.0225***	0.0068
Experience squared	0.0001**	0.0001	0.0002*	0.0001	0.0003**	0.0001
Household size	0.0025*	0.0014	0.0040	0.0026	0.0059*	0.0033
Farm size	-0.1235***	0.0121	-0.0722***	0.0217	-0.0836***	0.0267
Off-farm employment	-0.0435**	0.0193	-0.0652*	0.0356	-0.0831*	0.0440
Farmer group membership	0.0054	0.0325	-0.0182	0.0584	-0.0236	0.0739
Extension contacts	0.0100***	0.0026	0.0096**	0.0047	0.0110*	0.0058
Access to credit	-0.0403*	0.0236	-0.0534	0.0431	-0.0559	0.0535
Pest and diseases	-0.0060	0.0199	-0.0304	0.0357	-0.0526	0.0439
Constant	0.8318***	0.0527	0.9773***	0.0961	1.1119***	0.1259

Source: Author's calculations

Notes: ***, ** and * imply significant at 1%, 5% and 10% respectively. S.E. means standard error.

TE increased with household size at 10 per cent for the double bootstrap and Tobit models. This means that an increase in household members correlate with higher TE of the household. Larger households are less likely to be labour-constrained thus able to carry out farm operations timeously and more effectively to enhance TE. Similar result was attained by **Ahmadu & Alufohai (2012)** in an assessment of TE of rice producers in Nigeria.

The result further portrayed a decrease in TE with cultivated area implying that producers become more inefficient as their acreage increases. Smallholders typically cultivate small acreages and may lack the skills and managerial abilities to operate larger farms which may account for the decrease in efficiency as farm size increases. The results however disagree with that of **Asante *et al.* (2014)** which showed that TE of yam producers in Ghana's Brong Ahafo Region increased with farm size.

The results also showed that even though TE initially decreased with farming experience, it subsequently increased indicating that when farmers become more experienced in production, their efficiency level increases. As farmers become more experienced in farming, their level of efficiency is expected to increase. **Varasani *et al.* (2017)** observed an inverse association between years of farming and TE of groundnut farmers in India whereas **Danso-Abbeam *et al.* (2015)** obtained a positive connection between farming experience and TE of farmers in northern Ghana.

Participation in off-farm work was associated with lower TE, implying that off-farm engagement impacts negatively on farm efficiency. This could be due to labour-loss effect, as agricultural labour is lost to off-farm activities which could affect critical and timely farm operations. Other authors such as **Nkegbe (2018)** and Coelli et al. (2002) obtained similar inverse association between off-farm work and TE in their studies in northern Ghana and Bangladesh, respectively.

Access to agricultural extension had a positively significant influence on TE which is in sync with expectation. Extension workers play important roles in smallholder agriculture that helps to improve efficiency of production. For example, extension agents in Ghana train farmers in modern farming practices, introduce producers to new innovations and assist farmers to form groups and access farm inputs. The result resonates with that of **Abdulai *et al.* (2017)** and **Danso-Abbeam *et al.* (2018)** in their studies in northern Ghana.

Access to credit had a negative association with TE at 10 per cent level, and this was only in the case of the double bootstrap model. Low access to credit could account for the limited impact of credit on farmers' TE. **Anang *et al.* (2016)** observed that TE of rice farmers in northern Ghana was not different between credit users and non-users. **Nkegbe (2018)** however showed that credit users had higher TE than non-users in maize cultivation in northern Ghana.

Although, the traditional and bootstrap approaches produced different efficiency scores (70 per cent and 51 per cent respectively), the differences in scores do not seem to matter much if the focus is on second stage results (statistical significance of factors explaining TE scores). This result is very significant in DEA estimation. What the result implies is that while the application of bias-correction (bootstrapping technique) affects the magnitude of the TE estimates, it has little effect on the relationship between the efficiency scores and the exogenous factors influencing efficiency.

CONCLUSIONS AND POLICY IMPLICATIONS

The study compared three approaches for estimating the influence of exogenous factors on DEA scores through a data set related to small-scale farming in northern Ghana. TE estimation using the double bootstrap and traditional DEA approaches produced different efficiency estimates – 70 per cent for the traditional DEA and 51 per cent for the SW double bootstrap approach. In particular, the double bootstrap approach biased the TE estimates downwards.

The result further revealed that the double bootstrap and traditional DEA approaches yielded practically similar results regarding the influence of exogenous variables on TE within a semi-parametric framework. The results showed that due to sensitivity of the DEA approach to outliers as outlined by other authors, the traditional DEA approach overestimated the efficiency scores. What the result implies is that researchers measuring TE using DEA estimation should take into account the influence of the sensitivity of the DEA approach to outliers on the efficiency scores. However, despite the differences in efficiency scores for the traditional and bootstrap methods, the influence of exogenous factors on efficiency did not differ across the different approaches. The paper therefore demonstrated that bootstrapping largely affected the magnitude of the DEA estimates, but had little effect on the relationship between the efficiency scores and the exogenous factors influencing efficiency. Hence, for the purpose of identifying the sources of inefficiency in production, investigators may choose between any of the three estimators as they yield comparable estimates. Where investigators choose to simultaneously apply more than one estimator, statistically significant variables in the second stage regressions could be identified as potential policy instruments.

With regards to the policy implications of the study's findings, it is recommended that more female farmers should be encouraged to venture into groundnut production while extension services should be targeted at producers to improve their TE in order to promote household food and income security. Groundnut is an important food and cash crop in the study area. Empowering more women to venture into groundnut production is therefore expected to enhance the income of women farmers thereby improving household food and nutrition security. Extending extension services to smallholder farmers is essential to improve efficiency of resource use and farm performance in general. Extension service provision is also needed to increase the managerial abilities of producers. The results indicated that farmers became less efficient when their acreage increased. Thus, farmers lacked the managerial and technical abilities to manage larger acreage. Access to extension service is one of the critical factors that have enabled small-scale farmers in developing countries to acquire such managerial and technical skills to improve their level of production.

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REGULAR ARTICLE
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IMPACTS OF ADOPTING IMPROVED WHEAT VARIETIES ON HOUSEHOLD FOOD SECURITY IN GIRAR JARSO DISTRICT, ETHIOPIA

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ABSTRACT

Research Background: Access and consumption of adequate food are essential components of development goals. Agriculture is expected to play an important role in ensuring food security by increasing the availability of food at the household level. Ethiopia is attempting to enhance agricultural production and productivity to combat food insecurity.
Purpose of the article: The purpose of this study was to assess the impact of adopting improved wheat varieties on food security in Girar Jarso Woreda, Oromia Region, Ethiopia.
Methods: First multistage sampling techniques were used to select a target sample of 192 households, 90 adopters, and 102 non-adopters. Three kebeles were selected at random from Girar Jarso Woreda based on wheat crop cultivation. Primary and secondary sources were used to acquire both qualitative and quantitative data. The data was gathered through a household survey, key informant interviews with sample farmers, focus group discussions, and a review of reports. The researchers utilized a logit model to identify factors influencing wheat variety adoption, and the Household Food Balance Model (HFBM) was utilized to calculate net available food at the household level. A Propensity Score Matching (PSM) technique is also employed to quantify the impact of improved wheat varieties on households' food security.
Findings, Value-added & Novelty: The findings demonstrated that education level, involvement in training, demonstration, and field day events, distance to market, access to market information, and farmer cooperative membership all had a substantial impact on the adoption of improved wheat varieties. Hidase, Digelu, Dandeha, and Kubsa were improved wheat varieties planted by adopters in the study region during the 2017/2018 crop year. Adopting improved wheat varieties has the potential to increase food availability at the household level, which is a good indicator of food security.

Keywords: impact; improved variety; grain crop; household food security
JEL Codes: R52; R58; H41

INTRODUCTION

Access and utilization of adequate food are an indispensable part of developmental goals **(Sachs, 2012)**. Agriculture is anticipated to play a critical role in ensuring food security. Growth in agricultural production can minimize food insecurity by increasing the amount of food available for consumption at the household level **(Bogale, 2012).** Ethiopia is struggling to develop agricultural production and productivity to combat food insecurity.

Wheat is a basic food crop that is grown in both developed and developing countries and served as a source of food and cash. It has been the most grown cereal crop in the world, and the amount produced is more than that of other cereals, feeding around 40% of the world's population (**Acevedo *et al.*, 2018**). Wheat is an important cereal crop that helps to grow the agricultural sector in general and farm households' food security in particular **(Shiferaw *et al.*, 2013).** Ethiopia is a major wheat producer in terms of total wheat area grown and total production **(CSA, 2017).** Ethiopia's wheat production did not meet the national consumption, with the remaining obtained from imports **(Elias *et al.*, 2019).** This indicates that the country is still dependent on food imports, which requires high investment in the agriculture sector to close the demand gaps. Conducting extensive scientific studies can help to reduce the wheat yield imports. Cultivating local seeds with low disease resistance and low yield per unit area is common in rural areas. Crop disease has been restricted the potential wheat-producing regions, particularly Oromia regions of the country. Low adoption of improved varieties over time has been attributed to a range of circumstances that leads to low production that exposes an individual, household, community, and country to economic, psychological, and health-related stresses. As a result, food security and the adoption of improved varieties must be assessed concurrently.

The country has been focused on generating high-yielding, disease-resistant, and stable varieties that can fulfill the food demand for the growing population. The research system has been working on varietal development and seed replacement. Currently, more than 74 wheat varieties have been introduced in Ethiopia to satisfy the growing production demands of the population (**Anteneh & Asrat, 2020)**. Adoption of improved varieties can support the achievement of food security. Several studies suggest that better agricultural technology adoptions have a substantial positive influence on household food security **(Shiferaw *et al.*, 2014; Kassie *et al.*, 2014; Zewdie *et al.*, 2014)**. Improved technological adoption contributes significantly to food security by increasing yields and farm revenue **(Shiferaw *et al.*, 2014a; Khonje *et al.*, 2015)**. Disseminating productivity-enhancing agricultural technology is critical for fostering economic growth and alleviating food insecurity. Given this, the government of Ethiopia has been emphasizing the adoption of agricultural technologies to increase food security. Therefore, this study aims at assessing factors affecting the adoption of improved varieties. The study also evaluated the impact of improved wheat varieties adoption on the food security of farm households. It is expected that the findings will add to our understanding of food security and can also inform policy and action to address food insecurity.

LITERATURE REVIEW

Achieving food security is one of the priority issues in Ethiopia to sustain development efforts. Domestic food production has been below the requirements as a result of insufficient adoption of agricultural technology. There is a close relationship between food security and the adoption of agricultural technologies (**Spielman *et al.*, 2010)**. Generating and transfer of improved agricultural technologies in general and that of disease-resistant, and high-yielding wheat varieties is one of the pillars in the national food security strategy adopted by the Government of Ethiopia **(Shiferaw *et al.*, 2013).** Even though the Ethiopian government is struggling to implement agricultural technologies due to various factors, low-level adoption has been recorded.

Many factors influence the decision to utilize agricultural technology or practice. Farmers' decisions to adopt improved agricultural technologies are influenced by different socio-economic factors. Education, extension services, seed access, and field characteristics all play important roles in the adoption decisions of farmers **(Ghimire *et al.*, 2015).** Similarly, institutional factors such as government policy, prices, credit, input supply, land tenure, market, research, development, and extension activity have a role in farmers' decisions towards new agricultural technology. The adoption of improved agricultural technologies is affected by different institutional factors **(Suvedi *et al.*, 2017; Asfaw *et al.*, 2012; Abebaw & Haile, 2013; Abate *et al.*, 2016**). According to **Abate *et al.* (2016**), access to institutional finance has a considerable positive influence on both the uptake and extent of technology use. There are also environmental and market-related drivers for the adoption of agricultural technology. The adoption of agricultural technology is influenced by variables such as access to weather information, assets, and involvement in social organizations **(Wood *et al.*, 2014; Timu *et al.*, 2014; Lalani *et al.*, 2016).** Likewise, farmers' preference towards the technology influence the decision to use it **(Asrat *et al.*, 2010).** Many kinds of literature exist on determinants of adoption of improved agricultural technology by smallholder farmers in Ethiopia **(Abate *et al.*, 2016; Abro *et al.*, 2017; Abebaw & Haile, 2013; Abebe *et al.*, 2013)**.

There are also studies on assessing the impact of improved agricultural technologies on income and food security of households in Ethiopia **(Shiferaw *et al.*, 2014a; Asfaw *et al*., 2012; Tesfaye & Tirivayi, 2018; Habtewold, 2018). Leake & Adam (2015),** the use of improved variety is considered as the most important input for the achievement of agricultural productivity and food security status of farm households in Ethiopia. While success stories about an extension of wheat technology in Girar JarsoWoreda are to be expected, no published study on the impact of adopting improved wheat varieties on household food security has been identified (to the best of the author's knowledge). So far, research on the study area that has been done by **(Seyoum, 2016; Abi *et al*., 2020; Haile & Asfaw, 2018).** These investigations revealed the situation of poverty, income, and food security in Girar Jarso Woreda, but they did not go further to analyse the impacts of the adoption of agricultural technologies on food security.

DATA AND METHODS

The Study Area

The study was conducted on Girar Jarso *Woreda* in the North Shewa Zone of *Oromia* National Regional State of Ethiopia. Girar Jarso *Woreda is* located at a distance of 112 km from Addis Ababa, the capital city of Ethiopia, along the highway to Amhara National Regional State in the Northwestern direction. It shares borders with the Amhara Region in the North, Yaya Gullalle *Woreda* in the East, Debre Libanos *Woreda* in the South, and Degem *Woreda* in the West. Astronomically, the *Woreda* occupies $9^0$35'-$10^0$00'N latitude and $38^0$39'-$38^0$39'E longitude.

The *Woreda* has a total of 17 *Kebele*/peasant associations. The total population of the Woreda was 67,312 (34,467 males and 32,845 females). The total area cultivated was 21,401 hectares in the 2009E.C with an expected output of 599,454.6 quintals. Due to rusts, pests, climate change, and weed-related factors, the Woreda suffered 14 percent losses, with only 515,521.9 quintals of various crops were harvested. Aside from grain production, livestock husbandry is another source of income, with an estimated 108,972 cattle, 67,465 sheep, 23,929 goats, 3,611 horses, 589 mules, 26,331 donkeys, 115,447 chickens, and 3,067 traditional and contemporary beehives (report from WARDO, 2018).

Sampling

The probability sampling technique was employed to generate the desired sample size in the study area. A simplified formula provided by (**Yamane, 1967)** was used to determine the sample size. The desired sample size was obtained based on a 93% confidence level, 0.5=degree of variability, and a 7% level of precision (Equation 1).

$$n = \frac{N}{1+N(e^2)} \tag{1}$$

Where:
n the required sample size
N population size
e the level of precision

$$n = \frac{3334}{1 + 3334(0.07)2} = 192$$

The research was based on cross-sectional data on the 2017–2018 production year. A household cultivating a wheat crop at the kebele level is taken as the study's sample unit. The researchers followed three stages to select a sample of households. At stage one, a purposive selection of wheat crop-growing *kebeles* in the *Woreda*. In the meantime, the potential wheat production area was considered as a selection criterion. At a stage, two out of five identified wheat-growing *kebeles of* the *Woreda*, households cultivating wheat with improved and traditional/local seeds were identified in partnership with kebele leaders and development agents. Finally, at the kebele level, a sample of households was selected at random with a probability proportionate to the size of the sample. Based on this, 90 adopters and 102 non-adopter farmers were selected randomly from the three kebeles with a probability proportional to the sample size.

Data Collection Techniques and Instrument
The research was based on a combination of quantitative and qualitative research design. Both primary and secondary data sources were utilized. The primary data gathering involves the incorporation of household survey focus group discussion and key informant interview. Similarly, an observation technique was also utilized to verify the data. Secondary data collection was also employed, such as reviews of reports, published and unpublished materials, relevant literature, and organizational reports. To ensure data quality, data collectors were well-trained, questionnaires were pretested, logistic regression and PSM measuring models were employed and calibrated. In addition, completed surveys were checked daily. The enumerators were assigned to Kebeles where they did not work to decrease data bias, and the researcher observed and supervised them regularly.

Method of Data Analysis
Data were analysed statistically by using SPSS version 21 and STATA version 13. A Logit model is used to investigate factors influencing the adoption of improved wheat varieties. The study utilized Household Food Balance Model (HFBM) to quantify available food at the household level. A Propensity Score Matching approach was also used to measure the influence of improved wheat varieties on food security.

Measurement of Food Security
The Household Food Balance Model, which was created from the FAO Regional Food Balance Model via a modified form of a simple equation by (**Tolossa, 1996)** was used to compute the amount of food available at the household level.

The HFBM was used to calculate the net available gr ain food for the sample households in Girar Jarso *Woreda*. All variables needed for the HFBM model were transformed from local grain measurement units to kilogram grain equivalents. To compare what is available (supply) with what is needed (i.e., demand) grain food **(FDRE, 1996),** 2,100-kilocalories per person per day was used as a measure of calories required (i.e., demand) to allow an adult to enjoy a healthy, moderately active life A comparison of calories available and calories needed by a household was used to estimate a household's food security status (Equation 2)

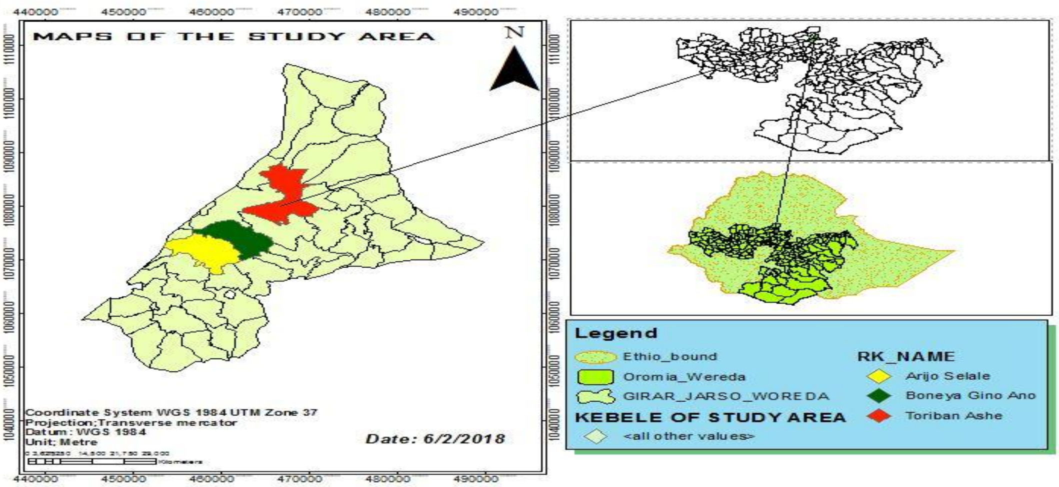

Figure 1: Map of the study area
Source: Ethio GIS (2007)

$$NGA_{ij} = (GP_{ij} + GB_{ij} + FA_{ij} + GG_{ij}) - (HL_{ij} + GU_{ij} + GS_{ij} + GV_{ij}) \quad (2)$$

Where:
NGA_{ij} Net grain available by i^{th} household in year j
GP_{ij} Total grain produced by i^{th} household in year j
GB_{ij} Total grain bought by i^{th} household in year j
FA_{ij} Quantity of food aid obtained by i^{th} household in year j
GG_{ij} Total Grain obtained through gift or remittance by i^{th} household in year j
HL_{ij} Post-harvest losses by i^{th} household in year j
GU_{ij} Quantity of grain reserved for seed by i^{th} household in year j
GS_{ij} Amount of grain sold by i^{th} household in year j
GV_{ij} Grain Given to others by i^{th} household in year j

Specification of the model

The study attempted to identify factors influencing the decision to use or not use improved wheat varieties by utilizing a logistic regression model. The factors were socioeconomic characteristics of households, agricultural extension service (training and extension contact), availability and accessibility of input, and market-related factors. If the response of the i^{th} farmer to the question of adoption was denoted by a random variable Y_i and a corresponding probability (i.e., probability of adopting improved variety or not by P_i such that the probability of adoption $(Y_i = 1) = P_i$ and the probability of non-adoption $(Y_i - 0) = 1 - P_i$

The logistic model is specified by Equation (3).

$$Y_i = \beta_0 + \beta_i X_i + U_i \quad (3)$$

Where:
Y_i be a dichotomous outcome random variable with categories 1(adoption) and 0 (non–adoption);
X_i denotes the collection of P - predictor variables;
U_i Denotes to the error term, which has an independently distributed random variable with a mean of zero.
In the regression model, the dependent variable in this case adoption is taking the value 1 or 0. The use of LPM has a major problem in that the predicted value can fall outside the relevant range of 0 to probability value. Therefore, the model was estimated by using Maximum Likelihood Estimation (MLE). So, the logistic cumulative probability function for adopters is represented by Equation (4).

$$P_i = \frac{1}{1+e^{-Z_i}} = \frac{e^{Z_i}}{1+e^{Z_i}} \cdots \quad (4)$$

Where:
P_i is the probability that the i^{th} farmer adopted the improved wheat varieties and that P_i is Non-linearly related to Z_i ($i.e. X_i$ and β_s)
$Z_i = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n$
e represents the base of natural logarithms.

Then, $(1 - P)$, the probability of non-adopter of improved wheat varieties is presented as Equation (5).

$$1 - P_i \frac{1}{1+e^{z}} \cdots \quad (5)$$

And then, by dividing Equation (4) by Equation (5), the odds ratio in favour of adopting the improved variety was obtained as Equation (6).

$$\frac{P_i}{1-P_i} = \frac{1+e^{Z_i}}{1+e^{-Z_i}} = e^{Z_i} \quad (6)$$

Then the dependent variable was transformed by taking the natural log of Equation (6) specified by Equation (7).

$$L_i = Ln\left(\frac{P_i}{1-P_i}\right) = Z_i = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n + U_i \quad (7)$$

Where:
L_i is the log of the odds ratio, L is the logit;
Z_i in the stimulus index, where P_i ranges between 0 and 1.

Propensity Score Matching

Propensity Score Matching estimates the average impact of the adoption of improved wheat varieties on adopters by constructing a statistical comparison group based on the probability of adopting in the treatment T conditional on observed characteristics X, given by the propensity score (**Rosenbaum & Rubin, 1983)**.

$$P(\chi_i) = Pr\,(T_i = 1 \perp X) \quad (8)$$

Where:
Y_i^1 the outcome of unit i if i were exposed to the treatment
Y_i^0 the outcome of unit i if i were not exposed to the treatment
$T_i \in \{0,1\}$ indicator of the treatment actually received by unit i
$Y_i = Y_i^0 + T_i\,(Y_i^1 - Y_i^0)$ the actually observed outcome of unit i and
X multidimensional vector of pre-determined characteristics or covariates (**Rosenbaum & Rubin, 1983)**. As a result, if the population of units denoted by i and the propensity score $P(X_i)$ is identified, the average effect of Treatment on the Treated (ATT)can be estimated as Equation (9).

$$T = E\,\{Y_i^1 - Y_i^0 \mid T_i = 1 = E\,\{E\,\{Y_i^0 - Y_i^0 \mid T_i = 1, p\,(X_i)\,\} = E\,\{E\,\{Y_i^1 | T_i = 1, p\,(X_i)\} - E\,\{Y_i^0 | T_i = 0, p\,(X_i)\}\,|T_i = 1\} \quad (9)$$

Where the external expectation is over the distribution of (p $(X_i)|T_i = 1)$, Y_i^1 is the potential outcome of the treatment, and Y_i^0 is an outcome of the control. Following (**Rosenbaum & Rubin, 1983**)the matching algorithms work with the following two strong assumptions: The first one is conditional independence /un-confoundedness assumption: this presumes that given a set of observable covariates X which are not affected by treatment, the potential outcomes are independent of treatment assignment: un-confoundedness, is that after controlling for covariates (X), mean outcomes of non-treated will be identical to outcomes of the treated if they had not received the program (**Rosenbaum & Rubin, 1983**).

$$\mathrm{Y}_i^1, \mathrm{Y}_i^0 \perp T_i, \mathrm{X}_i \quad (10)$$

This implies that selection is only based on observable characteristics and that all variables that influence treatment assignment and potential outcomes simultaneously are observed by the researcher (**Caliendo & Kopeinig, 2005**). (**Caliendo & Kopeinig, 2005**), further suggested that if the balancing hypothesis of un-confoundedness is satisfied, observations with the same propensity score must have the same distribution of observable (and unobservable) characteristics independently of treatment status. In other words, for a given propensity score, exposure to treatment is random, and therefore treated and control units should be, on average, observationally identical.

In this case, the treatment effects can be estimated by Equation (11).

$$\beta = \mathrm{E}\left(Y_i^1 \mid X_i, T_i = 1\right) - \mathrm{E}\left(Y_i^0 \mid X_i, T_i = 0\right) = \mathrm{E}\left(Y_i^1 - Y_i^0 \mid X_i, T_i = 1\right) + \mathrm{E}\left(Y_i^0 \mid X_i, T_i = 1\right) - \mathrm{E}\left(Y_i^0 \mid X_i, T_i = 0\right) = Y_i^1 - Y_i^0 \mid X_i, T_i = 1) \quad = \mathrm{E}\left(Y_i^1 - Y_i^0 \mid X_i\right) \quad (11)$$

Thus, because of conditional independence the selection effect=0, since

$$\mathrm{E}\left(Y_i^0 \mid X_i, T_i\right) = \mathrm{E}(Y_i^0 \mid X_i)$$
$$\mathrm{ATE} = \mathrm{ATET} \quad (12)$$

The second assumption is the common support assumption additional criterion besides independence is the satisfaction of overlap condition. It works with the trend of perfect predictability of D given X (Equation 13).

$$(\text{Overlap}) \quad 0 < P(T = 1 | \mathrm{X}) < 1 \quad (13)$$

It makes sure that individuals with the same X values have a positive probability of being both participants and non-participants (**Heckman & Smith, 1999**). Treatment units would therefore have to be similar to non-treatment units in terms of observed characteristics unaffected by the treatment; thus, persons that fall outside the region of the common support area would be dropped.

Estimation Strategy

If conditional independence assumption is satisfied and there is sufficient overlap between the two groups which is called ‘strong ignorability assumption’. According to **Rosenbaum & Rubin (1983),** the PSM estimator for ATT can be written in general as Equation (14).

$$\mathrm{ATT} = \mathrm{E}\, \mathrm{p(x)|T} = 1\{\mathrm{E}[\mathrm{Y}(1)|\mathrm{T} = 1, \mathrm{P(X)}] - \{\mathrm{E}[\mathrm{Y}(0)|\mathrm{T} = 0, \mathrm{P(X)}]\} \quad (14)$$

The Propensity Score Matching estimator is simply the mean difference in outcomes more than the common support, properly weighted by the propensity score distribution of adopters.

The dependent variable: is the adoption decision of improved wheat varieties. The variable takes the value of 1 for the household that cultivated improved wheat varieties during the 2017/2018 production year and 0 for the household that did not cultivate improved wheat varieties. Independent variable: Based on past research findings on the adoption of agricultural technology, major variables expected to influence the adoption of improved wheat varieties were selected. It is categorized under Household socio-economic characteristics, institutional and market-related factors. Farmers' adoption decisions were influenced by socioeconomic traits, institutional factors, and market-related factors **(Leake & Adam, 2015; Shiferaw *et al.*, 2014; Abebe *et al.*, 2016).**

RESULTS AND DISCUSSION

Socio-Economic Characteristics of Adopter and Non-Adopter of households

According to the findings (Table 1), 79 percent of respondents were male-headed, while 21 percent were female-headed households. 74% of adopters were male-headed households, whereas 26% were female-headed households. Non-adopter farmers were 83 percent male-headed and 17 percent of female-headed households. The Chi2-test showed that this association was not significant. The marital status of the household head revealed that 87 % of respondents were married. Disaggregated data among married farmers, 92 percent were adopters and 82 percent were non-adopters. Divorced farmers make up 6% of the sample of households, of which 2% were adopters and 9% were non-adopters. The Chi2-test indicated that the relationship was statistically significant at the 10% level.

Education can improve the use of agricultural technology. In terms of educational attainment, 34% of respondents were illiterate. The percentage differs greatly between adopters and non-adopters which is 23% of adopters and 44% of non-adopters were illiterate respectively. Non-formal education was scored by 46 percent of the total sample, with 46 percent adopters and 46 percent non-adopters. 20% percent of the total sample had primary education, with 31 percent adopters and 10 percent non-adopters. The Chi2-test showed that the relationship was significant at a 1% level. The result of the focus group discussion also revealed that adult education provided at farmer training centers by extension workers helps farmers to improve their capacity to read and write. Farmers' use of technology can be increased by educational attainment.

Farmers in the study area have been engaged in agricultural activities like crop cultivation, animal husbandry, and non-farm activities. Crop production is the primary source of income in the research area. Farming was a key occupation for the vast majority of the respondents. According to the findings, 82 percent of adopters and 81 percent of non-adopters engaged in agricultural activities. 18% of adopters and 18% of non-adopters engaged in both farm and non-farm activities. The Chi2-test showed that this association was not significant.

Age is an essential demographic attribute of the household head in deciding whether to use improved wheat varieties or not. The result in (Table 2) shows Adopters were on average 45 years old, whereas non-adopters were 46 years old. The t-test results show, there is no statistically significant difference in household age between adopters and non-adopters. The size of a farm also affects a household's choice of crops and improved agricultural technologies. The results showed that adopters had a larger average land size of 2.19 hectares compared to non-adopters, who had a mean of 1.9 hectares. The t-test result indicated that there is a 5% significant difference in total landholding between adopters and non-adopters. The total land size computed includes rented in, rented out the land, and sharecropping land. The larger land size of adopters is due to rent inland. The results from the focus group discussion also revealed that farmers who rented inland work more aggressively using agricultural inputs than those who never rented.

The mean household size of adopters and non-adopters is 6. In rural households, the higher number of households (working group) can contribute to the decision to adopt improved wheat varieties. The study area was also characterized by livestock rearing activities that include cattle, sheep, goats, pack animals, and poultry. The result of the study showed that non-adopters and adopters were found to own 7.88 and 8.26 of the Tropical Livestock Unit (TLU), respectively. The difference in livestock ownership among non-adopters and adopters was not statistically significant. This implies that having livestock is not correlated with adopting improved wheat varieties. This study is not in line with the study by Alemaw, 2014, which found a significant correlation between livestock ownership and the decision to adopt improved maize varieties in the Oromia region, Ethiopia.

Income from farms indicated that non-adopters had a lower mean farm income of Ethiopian Birr 17,479 compared to adopters, which is 37,321 Birr per season. The t-test result indicated there is a difference between adopters and non-adopters in terms of income from farm activities at a 1% significance level. At the same time, adopters had slightly more non-farm income at Ethiopian Birr 2,569 per season than the non-adopters, who had a mean of Ethiopic Birr 1,607 per season. The t-test result indicated there is a difference between adopters and non-adopters in terms of income from non-farm activities at a 1% significance level. The mean years of wheat farming experience of both adopters and non-adopters were 17 years. The t-test result also shows there is no difference between adopters and non-adopters in terms of wheat farming experience.

Institutional Characteristics of Rural Households

This study also tried to assess the awareness of respondents about agricultural extension services, particularly whether they possessed the required information and whether they needed the service (Table 3). The result on contact with extension agents indicated that 87% of adopters and 54% of non-adopters had contact with an extension agent. The Chi^2-test confirmed that the association in terms of contact with the extension agent was significant at a 1% level. Farmers' understanding of agricultural technology has increased as a result of the efforts of governmental, non-governmental, and social media organizations.

Field day and demonstration events were attended by 78 percent of adopters and 22 percent of non-adopters. Farmers were more interested in learning from field day activities than from regular meetings, implying that they were more interested in learning from field day activities. The Chi^2-test indicated that there is a significant association between adopters and non-adopters at a 1% significant level. In terms of training, the descriptive analysis revealed that 81 percent of adopters and 50 percent of non-adopters had attended the training. The more farmers that are trained, the more likely decide to use technology. The Chi^2-test confirmed that the association was significant at a 1% level. Farmers that are members of a farmer's cooperative profit the most. Farmers' cooperatives were represented by 68 percent of adopters and 20% of non-adopters. The results from the focus group discussion also revealed that farmers who were members of farmer cooperatives could access input technology more easily than non-members, and hence this could maximize the opportunities to use technology. The Chi^2-test showed that the association between adopters and non-adopters in terms of being a member of a farmer's cooperative was significant at a 1% level.

Concerning access to credit, both adopters and non-adopters had limited access to credit services. The result indicated that 7% of adopters and 10% of non-adopters had access to credit. Even though access to credit allows households to bridge budget gaps, both adopters and non-adopters in this research had limited credit service. The result from the focus group discussion also revealed that farmers did not take credit because they were afraid of payback. The Chi^2-test also indicates that there is no significant association between adopters and non-adopters in terms of access to credit. Creating a conducive environment for farmers in terms of infrastructure has played an important role in adopting technology. The more farmers have road access, the more they can easily access inputs. They may also offer their products on the market easily. The result indicated that 66% of adopters and 51% of non-adopters had access to vehicle roads. The Chi^2-test reveals that these associations were significant.

Market-Related factors

Distance to the market result shows that the adopters an average of 12 kilometers, whereas the non-adopters are expected an average of 10 kilometers at a significant level of association. The decision to use improved wheat varieties might be influenced by distance from the market. The cost of transportation is directly related to the distance to the market. A result of the key informant interview at Ilamu Kebele indicated that farmers paid 20 Ethiopian Birr/quintal for transport costs. This result is in line with the study by **Shiferaw *et al.* (2014b),** who found proxy distance to the output markets was positively correlated with improved varieties' adoption. The result of the price of wheat shows that adopters sell their product at a higher price of 1,231 Ethiopian Birr per quintal, while non-adopters sell at 1,154 Ethiopian Birr per quintal. This result confirmed that there is a difference between adopters and non-adopters selling the price of wheat grain at a 1 % significance level (Table 4). As stated in subsection three of this paper, a farmer's decision to adopt improved varieties is based on utilizing maximum utility. Therefore, we can deduce that the high price of wheat grain from improved seed is what triggers farmers' decision to use improved wheat varieties.

Table 1: Household characteristics of the adopter and non-adopters (dummy variable)

Variable	Category	Adopters Fre	%	Non-adopters Fre	%	Full sample Fre	%	Chi^2-test
Sex	Male	67	74.4	85	83.3	152	79.1	0.13
	Female	23	25.5	17	16.6	40	20.8	
Marital status	Married	83	92.22	84	82.35	167	87	0.087**
	Divorced	2	2.22	9	8.8	11	5.73	
	Widowed	5	5.56	9	8.82	14	7.29	
Educational status	Illiterate	21	23.3	45	44.2	66	34.38	0.000*
	Non-formal education	41	45.56	47	46.08	88	45.83	
	Formal education	28	31.11	10	9.80	38	19.79	
Occupation	Only own farming	74	82.2	83	81.4	157	81.8	0.642
	Farm and non-farm activities	16	17.8	18	17.6	34	17.7	

Note * and ** =significant at 1%and 10% respectively
Source: Field survey, 2018

Table 2: Household characteristics on continuous variables

Variables	Non –adopters Mean	SD	Adopters Mean	SD	t-test
Age (in years)	46	9	45	9	0.253
Total Land	1.779	.860	2.031	0.687	0.026**
Number of households	6	2	6	2	0.510
Farming experience	17	7	17	7	0.930
Livestock holding(TLU)	7.88	4.22	8.26	3.25	0.490
Income from farm per year	17479.53	13935.06	37321.88	24934.28	0.000*
Income from non –farm per year	1607.45	1281.49	2569.24	1716.46	0.000*

Note: * and ** =significant at 1%and 5% respectively
Source: Field Survey,2018

Table 3: Institutional Characteristics of the adopter and non-adopters

Variables		Adopters Frequency	%	Non-adopters Frequency	%	Chi^2–test
Contact with extension agent	Yes	78	86.6	55	53.9	0.000*
	No	12	13.3	47	46.08	
Participated in demonstration	Yes	70	77.7	22	21.5	0.000*
	No	20	22.2	80	78.4	
Attend in training	Yes	82	91.1	51	50.0	0.000*
	No	8	8.8	51	50.0	
Member of farmers	Yes	61	97.7	20	19.6	0.000*
	No	29	32.2	82	80.3	
Access to credit	Yes	6	6.6	10	9.8	0.433
	No	84	93.3	92	90.2	
Vehicle road access	Yes	59	65.5	52	50.9	0.041
	No	31	34.4	50	49.2	

Note * significant at 1%.
Source Field Survey, 2018

Table 4: Market-related factors among adopter and non-adopters

Variables	Non- adopters Mean	SD	Adopters Mean	t-test
Distance to the market	11	4	12	0.11
Price of wheat grain	1154	86	1231	0.00*

Note * and **=significant at 1%
Source: Field Survey, 2018

Access to market information plays an important role in the adoption of agricultural technologies. The result in (Table 5), indicates 62% of adopters and 52% of non-adopters had access to market information. The Chi^2-test result showed that there is no significant association between adopters and non-adopters in terms of access to market information.

Factors Affecting Adoption of Improved Wheat Varieties

A logit model is estimated to determine the factors influencing the adoption of the improved wheat varieties. Adoption of improved variety was affected by the technology's maximum utility **(Hagos, 2016; Asfaw *et al*., 2012)**. According to **Asfaw *et al.* (2012**), adopting improved varieties increased the chance of food security and had a beneficial influence on the cash wages of adopting families. **Leake & Adam (2015**), also found that the utilization of improved varieties is the most significant input for farm households in Ethiopia to attain agricultural production and food security. **Hagos (2016)** found, that 80 percent of farmers expressed a readiness to plant improved wheat varieties maximum utility. Based on this, a model containing 12 selected predictor interaction terms was included in the multivariate analysis. Using the stepwise (likelihood ratio) method, four of the twelve predictor variables (education status, participation in training, demonstrations, and field days, distance to the market, and member of a farmer's cooperative) have a significant joint impact on determining household adoption of improved wheat varieties. The overall model is proven, as it is statically significant at a p-value of 0.000. The pseudo-R-squared is found at about 0.3759, meaning all the explanatory variables included in the model explain 37% of the probability of a household's adoption of improved wheat varieties. The $LRCh^2$ (12) 99.77 with a P-value (Prob > ch2) 0.000 also tells us the logit model as a whole is statically significant. The signs of the regression coefficients of the model (Table:6) fulfil the underlying assumption and the corresponding p-values imply that the predictor variables included in the multivariate model have a significant joint influence on the outcome variable. The estimation variance inflation factor was done to test whether multi-collinearity problems exist or not. There was no explanatory variable dropped from the estimation model since no series problem of multi-collinearity was detected from the VIF results which are very far less than 10 and again those of the tolerance level (1/VIF) were greater than 0.2 which further revealed no problem of multicollinearity.

The marginal effect results provided in Table 6 show that keeping other factors constant, an increase in the level of education of a household by one year increases the probability of adopting improved wheat varieties by 0.23 (23%). Again, it is statically significant at a 5% significance level. The education status of a farmer had a positive and significant influence on the adoption of improved wheat varieties. Results from focus group discussion also revealed that better education attainment of farmers could increase the adoption of improved wheat varieties. This finding has conformity with other studies that found, the educational level of the household head can have a significant and positive effect on the adoption decision **(Asfaw *et al.*, 2012; Shiferaw *et al*., 2014; Leake & Adam, 2015)**. **Leake & Adam (2015)**, found that using the marginal effect increases the level of education by one year increases the level of adoption by 0.049 among the adopters.

From the analysis of marginal effects, households who participated in the training, demonstration, and field day practices were 56% more likely to adopt improved wheat varieties relative to those who did not participate. It is statically significant at a 1% significance level. Farmers are more interested in learning from other farmers' life experiences than they do in regular training. The result of the focus group discussion revealed that farmers learn more on-field days because the farmers share the life path of their farming experience at each step, so attending field days is positively and significantly related to the adoption of improved wheat varieties. The result is consistent with other studies that suggest participation in training and field days is one of the means of the teaching and learning process of improved technologies **(Bola *et al.*, 2014; Wondale *et al.*, 2016; Suvedi *et al.*, 2017; Davis *et al*., 2012).** Field days provide an opportunity for the farmers to observe how the new technology is practiced in the field. **Wondale *et al.* (2016)**, found the same result by using the logit model, in that attributes other being kept constant, the odds-ratio in favour of adopting improved varieties increases by a factor of 1.719 as a farmer ‘‘engagement in field days’’ increases by one unit. The study indicated that demonstration and dissemination of information through field day and demonstration activities might facilitate the adoption of improved wheat varieties.

Being a member of the farmer's cooperative of the household head was found to have a positive significant influence on the adoption of the improved wheat varieties. The result shows a one-unit increase in household participation as members of a farmers' cooperative. The probability of adopting improved wheat varieties increases by a factor of 0.43. It is statically significant at a 5% probability level of significance. This might be farmers' engagement in farmer cooperatives would improve the use of improved wheat varieties. The result is consistent with **(Wossen *et al.*, 2017; Awotide *et al.*, 2016; Ma & Abdulai, 2016; Khonje *et al.*, 2015)**. The result also shows that as the distance to the market becomes proximate, adoption of improved wheat varieties increases by 0.04 and it is statically significant at a 5% probability level of significance. This implies farmers near the main road can get transportation facilities easily and at a lower cost than those farmers who are far from the main road to put wheat grain on the market. This implies that access to market information about the demand and supply of wheat grain and its products highly motivates farmers to cultivate improved wheat varieties**.** The result is consistent with **(Abate *et al.*, 2016; Khonje *et al.*, 2015).**

Two sample T-test on outcome Variable before matching

The study employed a two-sample t-test to check whether the adoption of improved wheat varieties has a significant impact on household food security. The mean value of food availability for the treated group is 1728 and the control group is 889 cal per day (Table 7). This indicates the treated group is higher by 839 cal per day compared to the control group. The difference is significant at the 1% critical level.

Estimation of the Impact of Adoption of Improved Wheat Varieties on Food Security

This section describes the whole process of arriving at the impact of the adoption of improved wheat varieties on food security. The researcher estimated improved wheat varieties' production effect on food security based on the cross-sectional data available. To determine the impact of improved wheat varieties on food security, and to obtain the impact of improved wheat varieties on food security The Propensity Score Matching method was performed by using STATA Version 13. The main purpose in using Propensity Score Matching was to identify the Average Treatment Effect on the Treated (ATT). In the estimation data from the two groups, namely, adopters of improved wheat varieties and non-adopters of improved wheat varieties, households were grouped on the dependent variable that takes a value of 1 if the household cultivated improved wheat seed, otherwise 0.

Matching Adopter and Non-Adopter Households

Four main tasks should be completed before presenting the matching task. First, predicted values of adoption decisions (propensity scores) should be estimated for all households of adopters and non-adopters. It is to predict the propensity score of characteristics that are not affected by the treatment variable. Secondly, a common support condition should be imposed on the propensity score distributions of adopters and non-adopter households. The common support region is the area in which the maximum and minimum propensity scores of adopters and non-adopters are included. Thirdly, discarding observations whose predicted propensity scores fall outside the range of the common support region. After this, the identification of an appropriate matching estimator was done. Finally, a check of the balancing test is done to see whether the matching quality was satisfied or not.

Defining the common support region

From the total treated observations, 8 households (8.6%) are off support, while 82 households (91.3%) are on support, and all the control households are included in the common support region (Table 8).

Each treated unit is matched only with the control units whose propensity scores fall into a predefined common support region of the propensity score matching, which is [0.04585088, 0.90580642]. The ATT result shows that adopters of improved wheat varieties had an average availability of food of 856.715097kcal, which is 49% higher than the non-adopters of improved wheat varieties, which is significant at a 1% level (Table 9).

The result on (Table 10), shows the ps- test of all explanatory variables. A low R^2 value means that program households do not have many distinct characteristics overall, and as such, finding a good match between adopters and non-adopter households becomes easier. Also, the pseudo-R2 indicates how well the regressors explain the participation probability. After matching, there should be no systematic differences in the distribution of covariates between both groups, and therefore, the pseudo-R^2 should be fairly low **(Caliendo & Kopeinig, 2005**).

The ATT result is confirmed through checking the balancing "ps-test," which helps us to know how much bias was reduced. From the result, the p-pseudo R^2 is minimized to 0.030 after matching, and the mean bias is also minimized to 7.9, which indicates the matching was good (Table 11).

As shown in Figure 2, treated on support indicates, the farmers in the adoption group who found a suitable match, whereas untreated indicates non-adopters, and treated off support indicates the individuals in the adoption group who did not find a suitable match. The balancing procedure tests whether adopters and non-adopters have the same distribution of propensity scores, and if not, they need a check-up. When the balancing test failed, the researcher tried alternative specifications of the logit model as suggested by (**Khandker *et al.*, 2010)**. Therefore, in this study, a complete and robust specification that satisfied the balancing tests was carried out.

Matching adopters and non-adopters

To estimate the average treatment effect of the adoption of improved wheat varieties on food security, we have used different matching algorithms. These are nearest-neighbour matching, radius matching, kernel matching, and stratification matching **(Khandker *et al.*, 2010)**. Across all NNM, RM, KM, and SM matching methods, adopters have higher calories per day than non-adopters at a 1% significant level (Table 12). However, the researcher selects the radius and stratification matching methods based on large sample size for the control group and a significant t-Value. So, on average, treatment effects on the treated range from 826.140 cal per day, radius matching method, to 869.932 cal per day, stratification matching method, at a 1% significant level.

Table 5: Access to Market Information

Variables		Non-adopters		Adopters		
		Frequency	%	Frequency	%	Chi^2-test
Access to Market Information	Yes	53		5252		570.419
	No	49		4838		43

Source: Field survey, 2018

Table 6: Adoption decision of farmers on improved wheat varieties

Variables	dy/dx	Std. Err.	Z	P>|Z|
Sex	0.1973	0.1272	1.55	0.121
Age of HH head	-0.0001	0.00621	-0.03	0.977
Educational Status	0.2344	0.08124	2.89	0.004**
Total land holding	0.0634	0.0641	0.99	0.322
Household size	-0.0212	0.0341	-0.62	0.534
Contact with extension agent	-0.0713	0.14341	0.50	-0.619
Participation in training and demonstration	0.5683	0.14236	3.99	0.000*
Member of farmer cooperative	0.4367	0.11062	3.95	0.000*
Access to credit	0.1220	0.2176	0.56	0.575
Distance to nearest market	0.0417	0.1218	3.34	0.001**
Vehicle road access	0.0003	0.11598	0.00	0.998
Market information access	0.1246	0.11708	1.06	0.287

Number of obs = 192; LR chi2(12) = 99.77; Prob > chi2 = 0.0000;
Log likelihood = -82.825805; Pseudo R2 = 0.3759
Note: that * and ** are statically significant at 1 and 5 %respectively.
Source: Field Survey, 2018

Table 7: Two-sample T-test on cal per day before matching

Variable	Groups	Obs	Mean	Std. err	Std. dev	T-test
Cal per day	Treated	90	1728.621	97.21	922.247	0.000*
	Control	102	889.0735	35.991	363.4922	
	Mean difference		839.5477	99.00381		

Source: Field survey, 2018

Table 8: Common support region

Psmatch2 treatment assignment	Off support	On support	Total
Untreated	0	102	102
Treated	8	82	90
Total	8	184	192

Source: Field Survey, 2018

Table 9: ATT with common support range

Variable sample	Treated	Controls	Difference	S.E	T-stat
Cal-per day unmatched	1728.62117	889.07349	839.54767	99.003805	8.48
ATT	1748.22602	891.510923	856.715097	164.179908	5.22

Source: Field Survey, 2018

Table 10: Ps- test of independant variables after macthing

Variable	Mean Treated	Control	%bias	t-test T	p>|t |	V(T)/ V(C)
Sex	1.2317	1.2317	0.0	0.00	1.000	1.00
Age	44.707	45.915	-14.0	-0.88	0.381	1.01
Educational status	2.0244	1.9756	7.0	0.42	0.672	1.00
Total Land	2.1771	2.2195	-5.4	-.034	0.736	0.72
Family size	6.2805	6.4146	-8.4	-0.57	0.570	3.19*
Contact with agent	1.1341	1.1098	5.6	0.47	0.636	1.19
Access to training	1.0976	1.0854	3.0	0.27	0.788	1.13
Member of farmer cooperative	1.3415	1.3659	-5.6	-0.32	0.746	0.97
Distance to the nearest market	1.939	1.9634	-8.8	-0.72	0.471	1.62*
Access to credit	11.707	12.923	-12.5	-1.01	0.315	2.58*
Vehicle road access	1.3537	1.4634	-22.4	-1.43	0.155	0.92
Access to information	1.3659	1.3537	2.5	0.16	0.872	1.01

* if variance ratio outside [0.64; 1.55]
* if B>25%, R outside [0.5; 2]
Source field survey, 2018

Table 11: Mean bias Reduction after matching

Ps R^2	LR chi^2	P>chi^2	MeanBias	MedBias	B	R	%Var
0.030	6.76	0.873	7.9	6.3	40.8	1.16	25

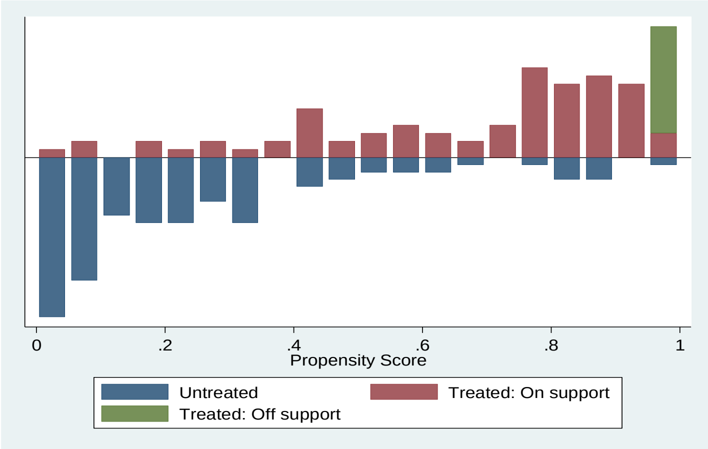

Figure 2: Histogram of propensity scores

Table 12: Average Treatment effect on the treated by the different matching algorithm

Matching	Number of treatment	Number of control	ATT	Std.Err	t-value
NNM	90	28	813.072	172.604	4.711
RM	90	81	826.140	100.400	8.228
KM	90	81	843.563		
SM	90	81	869.932	139.916	6.308

Source field survey, 2018

The result of the average treatment effect on the treated through radius and stratification matching methods indicates that the adoption of improved wheat varieties has brought a significant impact on adopters' household food security status. The Average Treatment Effect on the Treated (ATT) revealed that increment comes from the adopters' availability of food at the household level, which is a good indicator of a household's food security. This finding is consistent with (**Shiferaw *et al.*, 2014). Shiferaw *et al.*(2014a)**, found the same result by using both the Endogenous Switching Regression Model and the Propensity Score Matching method. The actual effect of adopters' experiences through adopting improved wheat varieties was Ethiopian Birr 976 of food consumption expenditure and a 2.7% binary food security outcome in Ethiopia. Likewise, the study is in line with studies **(Ahmed *et al.*, 2017; Khonje *et al.*, 2015; Kassie *et al.*, 2014b; Bezu *et al.*, 2014b). Kassie *et al.* (2014),** found that a one-acre increase in the level of maize adoption on average increased the probability of food security and per capita consumption in Tanzania. **Khonje *et al.* (2015),** also found that using both propensity score matching and endogenous switching regression models, adopting improved maize varieties results in considerable benefits in crop revenue, consumer spending, and food security.

CONCLUSIONS AND RECCOMENDATIONS

This study assessed the impact of adopting improved wheat varieties on food security among wheat farming households in Girar Jarso *Woreda*, Oromia region. From the study, it is possible to understand that adoption of improved wheat varieties is affected by different factors. Participating in training, field days or demonstration activities, educational status of the household head, and gender of the household head have positively contributed to the decision to adopt improved wheat varieties. In contrast, distance to the market and members of farmer cooperatives negatively affects the adoption of improved wheat varieties. This finding implies that creating a conducive production environment for farmers plays a vital role in the adoption of agricultural technologies.

The overall results are remarkably robust and the analysis supports the robustness of the matching estimator. From the findings, adopters of improved wheat varieties are significantly better than the non-adopters in terms of food availability at the household level, which is a good indicator of food security. From the findings of the study, it is possible to conclude that households who participate in training and field day, who have more access to market information, who have better educational status, and who have a shorter distance to the market tend to adopt improved wheat varieties. Similarly, it was found that households who could use the technology would improve the status of food availability and consumption. Overall, the adoption of improved wheat varieties significantly has a positive effect on the food security of rural households. The findings of the study are consistent with other study findings on the impact of technology adoption on food security **(Shiferaw *et al.*, 2014; Khonje *et al.*, 2015)**.

The results of the study give important evidence on the impact of agricultural technology adoption on improving food security in Girar Jarso*Woreda*, so governmental and non-governmental organizations in the study area should give due attention to the adoption of improved varieties to minimize the problem of food insecurity in the study area. Policy support, such as increasing market access and arranging field day programs to disseminate knowledge and information would aid in the adoption of improved wheat varieties. The government of Ethiopia should emphasize increasing access to and use of new wheat types to increase food security.

Future analysis using panel data may be needed to examine the relationship between the adoption of improved wheat varieties and food security, to control for unobserved specific heterogeneity, to provide more robust evidence on the implication of the adoption of improved wheat varieties for food security, and to see whether the result persists over time.

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INFLUENCE OF POSTHARVEST LOSSES ON HOUSEHOLD WELFARE AMONG AQUAFARMERS IN KENYA

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ABSTRACT

Research background: The trend in aquafarming has been increasing over the years, thereby meeting the deficit in fish production caused by capture fisheries. Aquafarming is a source of income and food for most Kenyan populations. Despite the increased fish production, postharvest losses in fish production have remained a challenge over the years. These postharvest losses resulted from high transport costs, poor preservation methods, inadequate storage facilities, and poor handling and mismanagement. The postharvest losses result in quality and quantity losses in fish production, thereby affecting the income received by farmers.
Purpose of the article: This paper analyses the effects of postharvest losses on household welfare among aquafarmers in Kenya.
Methods: Primary data was collected in Kiambu, Kirinyaga, Nyeri, Kakamega and Siaya Counties in Kenya. Semi-structured questionnaires were used to collect the data on a sample size of about 300 farmers. This study used a two stage least square was used to analyse the effects of postharvest losses on household welfare. Access to preservation facilities and distance to the market were considered instrumental variables in the model.
Findings & Value added: Results indicated that postharvest losses were negatively significant on household welfare. On the other hand, farmer's age, ownership of land, and the size of land under crop were also significant on household welfare. Due to inaccessible markets, postharvest losses result in to decline in farmers' income, hence welfare loss. The study recommended investment in preservation facilities and road infrastructure to reduce the number of postharvest losses in fish in an attempt to improve the welfare of farmers.

Keywords: aquafarming; household welfare; postharvest loss
JEL Codes: C12; C36; C83

INTRODUCTION

The global capture fisheries have been declining over the years due to increased fishing and high population growth (**Opiyo *et al.*, 2018**). On the other hand, aquaculture production has been rising over the years and has formed the large volume of fish consumed by humans. Aquafarmers have continued to experience high postharvest losses due to challenges in accessing the market (**Jacobi, 2013**). In the Second Medium-Term Plan (2013-2017) of the Vision 2030, the Government of Kenya emphasized the value of marine resources. The government introduced measures that ensured enforcement of fishing regulations and effective management practices to improve the potential for the fisheries and protect the biomass of fish. In addition, the blue economy blueprint, which is one of Kenya's Big Four Agenda, is a policy tool adopted in 2017 to help achieve the vision 2030 development agenda. The blue economy concept recommends methods for use in aquacultures such as cage culture (found in lakes, dams, ocean, and rivers), aquaponics or greenhouse, pens, breeding, and restoring commercially indigenous species **(Blue Economy, 2017)**.

Fish marketing is significant in poverty alleviation, food security, and sustainable agriculture **(Nyaga *et al.*, 2016)**. A study done by **Tesfey & Teferi (2017)** indicated that a colossal amount of postharvest loss resulted from inadequate storage facilities, poor handling and mismanagement, high transport costs, and outdated preservation methods. Without an assured market, large quantities of fish end up spoilt with implications on farmer's income, hence contributing to welfare loss **(Nyaga *et al.*, 2016)**.

Several efforts by the government of Kenya are primarily focused on the production side with less emphasis on marketing. These efforts are initiated because aquafarmers have continued to experience challenges in selling fish from their farms due to inadequate investment in the market, including storage facilities and preservation methods **(Nyaga *et al.*,2016; Meena, 2014)**. Hence, it limits the ability of the farmers to sell fresh fish, which attracts higher prices. Furthermore, organizing aquafarmers to access and actively participate in the market remains a significant challenge facing fish marketing **(Mohammed *et al.*, 2019)**. As a result, due to the highly perishable nature of fish, it has been observed that most aquafarmers have challenges accessing formal market outlets. The intermediaries have taken advantage and offered relatively lower prices for the fish, hence reducing farmers' household income. Therefore, this paper intends to analyse the influence of postharvest losses on household welfare.

LITERATURE REVIEW

According to **Diei-Ouadi *et al*. (2011)**, postharvest losses in the fisheries sector are highest among all other sectors. Postharvest losses in fish may result in financial losses since poorly processed fish or spoiled fish are sold or discarded at a low price. The low price leads to low household income. Since there is a high global demand for fish, a reduction in postharvest losses would significantly satisfy the consumer demand for fish through improvement in the quality and quantity of fish **(Opiyo *et al*., 2018)**.

Tesfay & Teferi (2017) carried out a study assessing fish postharvest losses in Tekeze dam and Lake Hashenge Fishery Associations in Northern Ethiopia. The results showed that the fishery associations were experiencing massive postharvest losses due to poor postharvest handling, poor storage facilities, and mismanagement. These postharvest losses contribute to Ethiopia's economic and nutritional waste, which was at risk of protein malnutrition. In addition, high postharvest failures lead to low household income and poor livelihood. **Tesfay & Teferi (2017)** proposed various measures to reduce postharvest losses, including introducing retaining cages, proper management of the refrigerators, decreasing fish harvest when refrigerators are already full, easy access to the storage area and refrigerated area. In addition, there is a need to have complete control of the refrigerators, and separating the spoiled fish from the healthy fish was proposed. The study also suggested that there should be careful treatment in handling and processing fish to increase the farmers' income. The study found that preservation is an essential aspect of the fishery associations.

A study was carried out by **Cole *et al*. (2018)** on postharvest fish losses. Unequal gender relations in Zambia revealed that 65 percent of the fish extracted from capture fisheries was processed using the open-air sun drying technique and the smoking methods due to inadequate cold chains and longer distance between the point of harvest and the market. The results showed that women were experiencing three times more physical losses than men. Fish losses among the fish value chain actors averaged 29.3 percent, with the quality losses at 22.9 % and the material losses at 6.4%. **Diei-Ouadi *et al*. (2011)** indicate that in Sub-Saharan Africa, the majority of the fish losses are quality losses; hence, there is a need to reduce postharvest losses that would improve household income.

Bolorunduro & Adesehinwa (2005) studied the status of awareness and adoption for the disseminated improved postharvest fisheries technologies among the fish processors in the North-western Zone of Nigeria. The study revealed that only 43.1% of the respondents knew about improved fish smoking kilns disseminated in the zone. Some of the constraints associated with this improved technology include scarcity of the kilns, high prices for the kilns, and technical features that were difficult to understand. These enhanced fish processing technologies can reduce postharvest losses, resulting in increased household income.

DATA AND METHODS

Study Area

This study was conducted in Kenya in five counties, including Kiambu, Siaya, Nyeri, Kirinyaga, and Kakamega. These counties were selected since they offer provide market for fish, have high population that is potential for fish consumers. Furthermore, these counties have favourable climatic conditions necessary for aquaculture production. Figure 1 shows the map of the study area.

Sample size

The sample size was determined using the formula given by **Kothari (2004)** (Equation 1).

$$n = \frac{z^2pq}{e^2} \qquad (1)$$

Where: n desired sample size; z the critical value (1.96) obtained at 95 percent confidence level; p the proportion of the population of interest (0.5). It is set at 0.5 to get a reliable and sufficient estimate; q the weighting variable; $1 - p$ and e *is* the acceptable error.

Kothari (2004) accepts an error of less than 10 percent; thus, this study used an error of 0.0566, which is precise hence a smaller sample size that could fit the budget for the study.

$$n = \frac{1.96^2 0.5*0.5}{0.0566^2} = 299.79$$

This was approximated to get a sample size of 300 fish farmers. The farmers to be interviewed were calculated using the population size in the various counties according to the data from Kenya National Bureau of Statistics, 2009 **(KNBS, 2019)**.

Table 1: Distribution of Sample size in the Counties

County	Population	Percentage in proportion	Number of Households
Nyeri	693,558	12.98	39
Siaya	842,304	15.75	47
Kiambu	1,623,282	30.35	91
Kirinyaga	528,054	9.87	30
Kakamega	1,660,651	31.05	93
Total	5,347,849	100	300

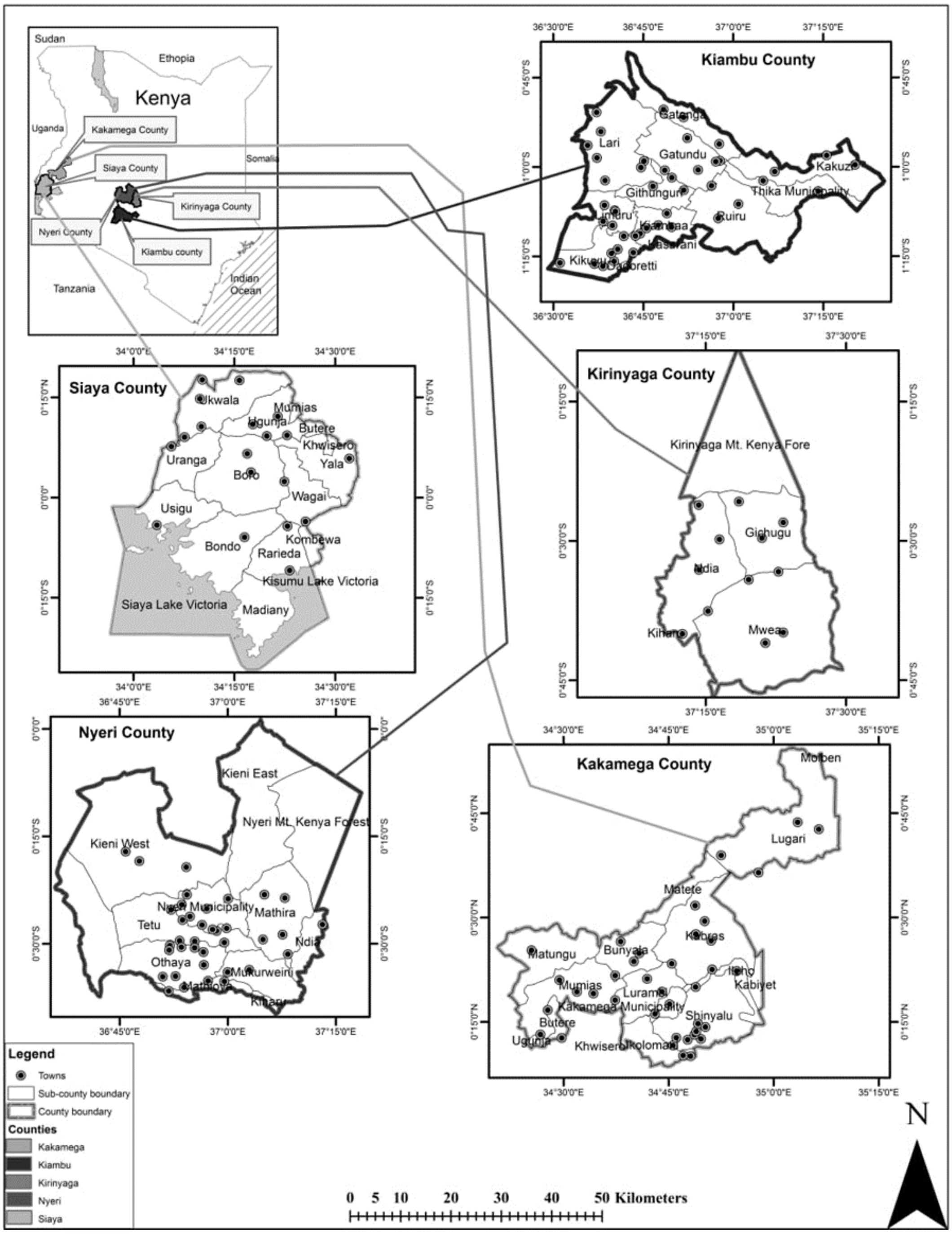

Figure 1: Map of the study area

Empirical Model

This study used the instrumental variables (IV) method, specifically the two-stage least squares (2SLS) regression analysis. Household income was used as an indicator of household welfare. While other indicators of measuring household welfare include true welfare indexes, total household expenditure, and total household income, this study preferred the total household income since it is simpler to use. The IV method is used in handling models with endogenous explanatory variables. It is used when at least one of the right-hand side variables in a regression model is correlated with the error term. This method was appropriate given the possible reverse causality between postharvest loss and household income. The Ordinary Least Squares (OLS) technique cannot be used in this case, given the apparent violation of the exogeneity assumption. The influence of postharvest losses on household income cannot be predicted directly since postharvest loss is an endogenous variable hence the use of the IV method.

2SLS is a method that uses the instrumental variables in computing the estimated values for the predictors' variables (first stage); the calculated values are then used in the second stage to assess the dependent variable's linear regression model. A valid instrumental variable must be correlated with the endogenous variable but not with the error term. In the first stage of the 2SLS, the instruments including preservation, distance, and access to value addition were regressed on endogenous explanatory variable (postharvest loss) in computing the estimated predicted postharvest loss. The first stage equation of the 2SLS was represented by Equation (2).

$$R_i = \beta_0 + \beta_i X_i + \beta_i Z_i + \lambda_i \qquad (2)$$

Where: R_i represents postharvest loss; β_0 constant; β_i vector of parameters; X_i exogenous variables, including age, years of education, gender, household size, distance to the market, land size under crop, land size under aquaculture, linkages to fingerlings market, access to income from other businesses and access to income from off-farm labour. Z_i instrumental variables, including preservation and distance to the market; λ_i the error term.

The predicted value of the postharvest loss was therefore used in the second stage to estimate the influence of postharvest losses on household income, as illustrated in Equation (3). The predicted value obtained in stage one replaced the endogenous variable. OLS was then applied to the structural equation to get consistent estimates of the parameters.

$$Y_i^* = \alpha_0 + \alpha_i X_i + \alpha_i\, prdctpsthlos + \mu_i \qquad (3)$$

Where Y_i^* represents household income, *prdctpsthlos* is the predicted postharvest loss; α_0 and $\alpha_i X_i$ are the coefficients to be estimated and μ_i is the error term.

Diagnostic tests

A test to check the multicollinearity that was conducted to verify the validity of the model was carried out. In detecting the presence of multicollinearity, variance inflation factor (VIF) was used to test for correlation between two or more independent variables and the strength of correlation. VIF value of 1 is good for the model since it indicates no correlation between the independent variables. VIF values between 1 and 5 show moderate correlation, which requires no measures to be taken. On the other hand, a VIF value of more than 5 indicates a critical value of multicollinearity. Some potential solutions to solve multicollinearity are combining independent variables linearly and analysing highly correlated variables, including partial least squares and principal component analysis. Durbin and Wu-Hausman test was used to test for endogeneity. F-test was used to test for the validity of the instrument. Good instruments satisfy the condition (Equation 4).

$$\mathrm{Cov}(Z_i, \varepsilon_i) = 0 \qquad (4)$$

Z affects Y only through X.

Bad instrument, however, satisfies the condition in Equation (5).

$$\mathrm{Cov}(Z_i, \varepsilon_i) \neq 0 \qquad (5)$$

Where β_{IV} need to be asymptotically inconsistent.

Sargan test was used to test for over-identifying restrictions validity of the instrument, while Basman test was appropriate in testing for over-identification.

RESULTS AND DISCUSSION

Two-stage least square was used to examine the influence of postharvest losses on household welfare, where household income was used as a proxy. The variables included in the model include gender, age, education level, household size, land size under crop, land size under aquaculture, access to off-farm income, ownership of land, linkages with fish market, and linkages with feed market facilities. The likelihood ratio test in the model (Chi2 (11) = 261.43) probability > Chi2 =0.0000) was significant, indicating that the association between the independent variables was statistically significant. R-Squared and Root Mean Squares of Errors (RMSE) were the determining coefficients of the model. Results indicated an R-squared value of 52.35 percent, implying a higher percentage of variability of the dependent variables. However, the 2 SLS model does not consider the number of variables used to fit in the model. Thus, RMSE was deemed to be appropriate. The RMSE was 80.12 percent; hence the model was fit.

Durbin and Wu-Hausman tests were conducted in testing for endogeneity, where Durbin (score) Chi2 (1) = 7.14422 (p= 0.0075) and Wu-Hausman F (1,253) = 6.98261 (0.0087). These p values were less than 0.05; the null hypothesis was rejected, indicating that postharvest loss was endogenous in the model. Hence, we can rely on the results of the two-stage least squares, in addition to postharvest losses, age, land size under crop, and ownership of land significantly affected household income.

Access to preservation facilities and distance to the market were used as instruments in the model. In testing for the strength of the instruments, results indicate that the partial R-Square was 54.31%, which implies that the variables still fit the model after excluding the instruments. The F statistics (25.70) were more significant than any of the critical values in Table 2; thus rejecting the null hypothesis that the instruments were weak; hence the instruments were considered strong.

Sargan and Basman tests were used in testing over-identifying restrictions. The p values for Sargan and Basman tests were 0.3542 and 0.3654, respectively. The p values were larger than 0.1, indicating failure to reject the null hypothesis of no over-identifying restrictions, implying that the model was well specified. Table 3 presents the results of the first stage of the 2SLS model. Access to preservation facilities and distance to the market were treated as instruments of postharvest loss. Results indicate that both access to preservation facilities and distance to the market was significant in the first stage regression of 2SLS. In terms of access to preservation facilities, studies indicate that preserved food products are more stable, permit high diet diversity, improve the level of digestibility, and give buyers the ability to choose a variety of products as well as a range of vitamins and minerals **(Kiaya, 2014)**. As a result, this increases the willingness of the traders to purchase from farmers with preserved fish since most buyers prefer them.

Distance to the market was positively significant on postharvest loss. The positive relationship implies that a longer distance to the nearest market translates to a longer time to transport fish. Studies reveal that farmers would choose marketing points near the farm as long as they are more accessible **(Bardhan *et al.*, 2012)**. The finding by Ismail and **Changalima (2019)** indicated that the mode of transportation determined the number of postharvest losses in agricultural commodities, which affected profitability. Similar research by **Sheahan & Barrett (2017)** noted that poor road infrastructure is attributed to high postharvest losses in most sub-Saharan countries. This finding is closer to the study by **Ansah *et al.* (2018)**, which established that postharvest loss management positively influences the welfare of farmers. This study found other factors, including household size and land size under aquaculture, positively impacted postharvest loss. In contrast, the study found the age of the household head and ownership of farms for aquaculture negatively significant on postharvest loss. Table 4 presents results on the influence of postharvest loss on household welfare.

The results presented above in Table 4 indicate that the coefficient of postharvest loss was negative and statistically significant at a 1 percent level. It shows that a unit increase in postharvest losses decreases farmers' income by 0.1 percent. This finding aligns with the earlier assumption that farmers with high postharvest losses are more likely to have low household welfare **(Getu *et al.*, 2015)**.

Table 2: Testing for weak instruments

Variable	R-Squared	Adjusted R-Squared	Partial R-Squared	F(2,253)	Prob > F
postharvestloss	0.2345	0.1982	0.5431	25.69966	0.0038

Minimum eigenvalue statistic = 25.69966				
Critical Values	# of endogenous regressors:1			
Ho: Instruments are Weak	# of excluded instruments:2			
2SLS relative bias	5%	10%	20%	30%
	(not available)			
	10%	15%	20%	25%
2SLS Size of nominal 5% Wald test	19.93	11.59	8.75	7.25
LIML Size of nominal 5% Wald test	8.68	5.33	4.42	3.93

Source: Field Survey, 2018

Table 3: Results of First of Stage Least Squares Regression

postharvestloss	Coef.	Std.Err.	P>|Z|	95% Confidence Interval	
Gender	-152.685	114.771	0.185	-378.714	73.344
Household size	24.909*	13.344	0.063	-1.371	51.188
Age	-5.699*	3.051	0.063	-11.709	0.310
Ownership of land	-488.109***	79.728	0.000	-645.123	-331.095
Access to off-farm income	-28.050	90.111	0.756	-205.512	149.412
log_landsizeaq	47.0549***	16.607	0.005	14.34914	79.76065
log_landsizecrop	72.864	60.549	0.230	-46.380	192.109
Linkages with fish market	61.318	101.863	0.548	-139.289	261.926
Linkages with feed market	66.2099	78.608	0.400	-88.599	221.019
Education level	5.091	11.483	0.658	-17.524	27.705
distance	2.429 ***	0.787	0.002	0.879	3.979
Access to preservation	-144.706**	88.639	0.014	-319.270	29.858
_cons	468.417	246.308	0.058	-16.658	953.493

Table 4: Results of the Two Stage Least Squares

log_household income	Coef.	Std.Err.P>|Z|	95% Confidence Interval	
Postharvest loss	-0.001***	0.0000.000	-0.002	-0.001
Gender of the farmer	-0.033	0.1590.838	-0.344	0.279
Household size	0.012	0.0200.541	-0.027	0.052
Age	-0.011**	0.0050.015	-0.020	-0.002
Ownership of land	0.583***	0.2220.009	0.148	1.018
Access to other business	-0.067	0.1150.560	-0.292	0.158
log_landsize aquaculture	0.037	0.0270.169	-0.016	0.090
log_land size crop	0.153*	0.0810.059	-0.006	0.312
Linkages with fish market	-0.136	0.1310.301	-0.394	0.122
Linkages with the feed market	0.018	0.1020.858	-0.181	0.217
Education level	0.013	0.0150.372	-0.016	0.043
_cons	13.065***	0.3460.000	12.387	13.742

Number of observations = 300

Wald Chi2 (12) = 345.83 Prob> chi2 = 0.0000 R-squared = 0.6625

Root MSE = 0.67437

Note: *, *** represents 10% and 1 % significance levels, respectively

The time between the harvesting of fish, preservation facilities, and delivery to the final marketplace determines the number of postharvest losses. These losses result in quantity losses, resulting in the low volume of fish available for sale and quality losses leading to low household income. As a result, inadequate storage and preservation facilities expose fish to damage before reaching the market.

Age of the farmer was found to be negatively statistically significant at a 5 percent level. An increase in the farmer's age by a year decreases the household income by 1.1 percent. A plausible reason is that younger farmers are receptive to new ideas in the market and are less risk-averse; hence they would probably take new ideas related to fish production and marketing. This finding ties with **Langyintuo & Mungoma (2008)** study that as the farmer gets older, they usually become risk-averse; hence they will not be willing to venture into new areas that they are not sure of. At the same time, younger farmers are more flexible in their decision-making process in adapting to new farming practices.

Results indicate that access to land ownership increases household income by 58.3% at a 1% significance level. Land ownership is related to crop, livestock, and aquaculture production. Land ownership is expected to influence aquaculture activities and income generation activities. Farmers who own good proportions of land can access credit and thus diversify into various income-generating activities, including non-farm activities. The results are similar to the findings by **Winters *et al.* (2017)**, which indicate that improved land access is directly linked to agricultural production hence would improve household welfare.

Land size under crop was found to influence household income at a 1% significance level positively. Results indicate that a unit increase in land size increases household income by 15.3%. A plausible reason is that increase in farm size increases the output per unit of labor which translates to higher total income by the farmers. Medium-sized farms are more commercialized than small farms in both input market participation and sale of the output. This finding confirms the results obtained by **Noack and Larsen (2019)**, which indicate that farmers with large farm sizes are more likely to have more income.

CONCLUSIONS AND RECCOMENDATIONS

The findings indicate that postharvest loss is an endogenous variable on household welfare. The study found access to preservation facilities and distance to the market influenced the amount of postharvest loss. Results indicate that postharvest loss negatively affects household welfare, implying that reduced postharvest losses lead to high household income hence increased household welfare. The study found out that age of the farmer negatively influenced household welfare. On the other hand, land ownership and land size under crop are positively significant on household welfare.

The study offered opportunities to farmers to meet the local demand for fish through aquafarming. The policy should include having many extension contacts, training, and providing credit to farmers to enhance fish marketing. The government needs to increase the provision of title deeds to increase the number of farmers who own land rights. Title deeds act as collateral when one needs to apply for credit in banks and other financial institutions. As a result, farmers would be able to have resources that are necessary for postharvest loss management.

To reduce postharvest losses among farmers, the government needs to invest in preservation facilities and low-cost processing technologies that address quality without moving up fish prices. Different private actors, including commercial banks and Sacco’s, need to facilitate the postharvest value chain in fish by increasing credit access through providing loans to farmers that would make them invest in storage facilities. As a result, this would minimize the areas of postharvest losses.

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HOUSEHOLD DEMAND SYSTEM OF AFRICAN INDIGENOUS VEGETABLES IN KENYA

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ABSTRACT

Research background: Vegetables are important sources of nutrition to many households. Understanding the household demand system of leafy African indigenous vegetables (AIVs) in Kenya could enhance designing strategies to increase their consumption levels.
Purpose of the article: The study was conducted to evaluate the effects of demographic variables on budget shares for commonly consumed leafy vegetables and to generate vegetable demand elasticities.
Methods: A stratified multi-stage sampling approach selected 168 and 282 respondents in rural and urban areas, respectively. The study used primary data, and a Linear Approximate Almost Ideal Demand System was estimated using the Seemingly Unrelated Regression method.
Findings, value & novelty: Own-price elasticities indicated that leafy AIV crops are normal goods. Cross-price elasticities indicated leafy AIVs are more complementary to each other and can be substituted for the consumption of exotic vegetables. The price effect could substantially contribute to changes in demand than would income. Vegetable demand could still increase with a future increase in household income. Expenditure elasticities classified cowpea (*Vigna unguiculata* L. Walp.) and spider plant (*Cleome gynandra* L.) as necessary vegetables. Results can be used to develop strategies for increasing demand for leafy AIV crops, thus enhancing consumption of healthy diets.

Keywords*:* consumer demand; Kenya; LA/AIDS; vegetable consumption
JEL Codes: C31; D11; D12; D13

INTRODUCTION

African indigenous vegetables (AIVs) are crops whose natural habitat originated in Africa and integrated into cultures through natural, or selective, processes (**Schippers, 2002; Maundu *et al.*, 2009**). They contain adequate micronutrients and health-protecting properties (**Smith and Eyzaguirre, 2007; Singh *et al.*, 2013**) and are essential sources of food security, income, and employment (**Shackleton, 2003; Jansen van Rensburg *et al.*, 2007**).

Leafy AIV crops are hardy species and can be helpful for production in less than optimal production areas. The growth cycles of different vegetables make some of them available at other times of the year (**Mumbi *et al.*, 2006; Onim and Mwaniki, 2008**). They have the potential to correct micronutrient deficiency in developing countries. Their retail prices are affordable to low-income households who regularly depend on leafy AIVs to fulfil daily micronutrient requirements (**Weinberger and Msuya, 2004; Asian Vegetable Research and Development Center (AVRDC), 2006; Kwenin *et al.*, 2011**). Their diversity, supply, and consumption level are high during rainy seasons. During dry spells, reduction in AIV consumption is higher in poor-rural households due to low disposable income (**Weinberger and Msuya, 2004; Durham and Eales, 2006; Powel *et al.*, 2009**). Low-income families in developing countries spend a large proportion of their income on food. A small fraction of food expenditure is allocated to vegetable purchases (**Kamau *et al.*, 2011; Otunaiya and Shittu, 2014**). An indication that AIV's role in consumer diet seems marginal, especially among poorest households, and vegetables are regarded as luxuries (**Van der Lans *et al.*, 2012; Ogundari and Arifalo, 2013**).

The introduction of exotic vegetables in Africa was supported by development agencies and linked to urban or modern lifestyles and high self-esteem (**Schippers, 2002**). Food habits changed against the consumption of AIV crops, which were neglected and associated with rural-poor people (**Gotor and Irungu, 2010**). Despite the abandonment, there has been renewed interest in their production, marketing, and consumption. Several interventions have enhanced AIV consumption, and their market share and demand level has been increasing (**Smith and Eyzaguirre, 2007**).

Farmers and farmer groups, in collaboration with development agencies, and government extension services, have responded to emerging market opportunities created by increasing AIV demand. However, studies in sub-Saharan Africa indicates that the market demand for leafy AIV crops is high, especially in urban areas (**Ruel *et al.*, 2005; Mwangi and Mumbi, 2006; Ngugi *et al.*, 2007; Muhanji *et al.*, 2011**). Moreover, a high market potential still exists due to increasing populations, urbanization, and possibilities of intensifying interventions in delivering leafy AIVs to nearby urban centres (**Ngugi *et al.*, 2007**). Understanding a complete demand system for leafy AIV crops is vital in designing strategies for exploiting their full potentials in developing countries. Besides price, income, diversity, and seasonality, some studies indicate demographic variables are important factors in explaining vegetable demand patterns (**Ogundari and Arifalo, 2013; Ayanwale *et al.*, 2016**).

Ruel *et al.* (2005) used an Almost Ideal Demand System (AIDS) model but did not wholly disaggregate vegetables into discrete crops. Although **Bundi (2012)** completely disaggregated vegetables using the AIDS model, AIVs were not part of this analysis. The only study that came close to the present research is **by Amaza (2009)**, which analysed the demand for traditional African vegetables and sweet potatoes in Kenya and Tanzania. However, the weak separability assumption was violated, and selectivity biasness resulting from zero consumption responses was not corrected in the analysis. Effects of demographic variables on vegetable demand have been previously not evaluated. Demographics capture differences in consumer characteristics, influencing household economic response to food consumption (**Pollak and Wales, 1981; Dudek, 2010**).

The objective of this study was to evaluate the household demand system of leafy AIVs. This involves examining vegetable demand behavior of households at finer level of disaggregation by estimating price and income elasticities of commonly consumed vegetables in Kenya. For comparison purposes, exotic leafy vegetables were included in the analysis. The uniqueness of this study is the integration of demographic variables, correcting for selectivity bias, and completely disaggregating vegetables into independent crops using a complete demand systems approach.

Theoretical framework

The theoretical framework is a household based model. However, the study assumes that households are net consumers and have no preference for the products they intend to produce for consumption. Thus, the Marshallian demand function is best fit because most households are market based environment and not producer based market informed. From Random utility theory, primal and duality approaches can be used to estimate demand functions. According to **Varian (1992)**, primal preference approach is derived from utility maximization theory, where utility is expressed as a function of price and income. The approach assumes rational consumers selects a preferable bundle of goods from a set of affordable alternatives, given a budget constraint. In this regard, direct utility is expressed as a function of quantities of goods consumed subject to a budget line as shown in Equation (1).

$$Max\ U = U(Q) \quad s.t \quad M = \sum_{k=1}^{n} p_k\, q_k \tag{1}$$

where; Q is a vector of n goods demanded, M is fixed consumer income (total expenditure), and $P = (p_1, p_2, \dots \dots .. p_k)$ is a vector of prices for goods $1,2, \dots .k$ demanded. From utility maximization framework, derived demand for each good is obtained using Lagrangian method (Equation 2).

$$\mathrm{L}(\mathrm{Q}, \lambda) = U(Q) + \lambda(M - \textstyle\sum_{k=1}^{n} p_k\, q_k) \tag{2}$$

Where: λ is Lagrangian multiplier (marginal utility of income). Deriving first order condition with respect to q_i and λ, and subsequently solving the resulting equations simultaneously with respect to q_i , Marshallian or uncompensated demand function is obtained using Equation (3).

$$\left.\begin{matrix} q_i = \emptyset_i(P,M) \\ Q^* = \emptyset_i(P,M) \end{matrix}\right\} \tag{3}$$

Where: q_i and Q^* is Marshallian demand function for good i and for the entire set of goods demanded, respectively. Substituting Equation (3) into Equation (1), an indirect utility function is obtained by Equation (4).

$$U^* = V(P, M) \tag{4}$$

Where: $V(P, M)$ is the maximum utility attainable at given prices and income level.

On the other hand, duality theory assumes utility maximization is derived from expenditure or cost minimization. In this approach, expenditure is expressed as a function of utility and price. The objective function under duality is given as Equation (5).

$$MinU = M = \sum_{k=1}^{n} p_k\, q_k \qquad s.t \qquad U = U(Q) \tag{5}$$

Adopting Lagrangian procedure, optimal values of Q are obtained, which are denoted as Equation (6).

$$U^* = h(U, P) \tag{6}$$

Equation (6) is Hicksian or income compensated demand function (**Varian, 1992**) implying that holding utility fixed, Q is influenced by a vector of prices for goods demanded.

DATA AND METHODS

Study area and sampling design

The study used a stratified multi-stage sampling approach to select respondents who were interviewed at retail outlets after purchasing leafy vegetables. In the first stage, Nairobi, Nakuru, Kisii, and Kakamega counties in Kenya were purposively sampled. Kisii and Kakamega are among rural counties with large AIV production levels, while Nakuru and Nairobi are among urban counties with final markets, where AIVs from different production zones are sold. The second and third stages were stratified based on information obtained from sub-county agricultural offices. In the second stage, one sub-county from each county, identified as significant areas where large volumes of AIVs are produced or consumed, was chosen. The third stage involved stratification of market outlets. In urban areas, markets were stratified into supermarkets, green groceries, and local open-air retail outlets. In rural areas, farm gates, green groceries, and local open-air retail outlets were classified. In the fourth stage, simple random sampling was used to select an equal number of respondents from each retail outlet. Ultimately, 450 respondents were selected, distributed proportionately to population size at the county level, resulting in 168 and 282 respondents in rural and urban areas, respectively. Responses to the semi-structured questionnaire through face-to-face interviews were obtained in July 2015. The questionnaire was designed to elicit information on the price and quantities of commonly consumed leafy vegetables in the study area and on demographic variables including; location, age, gender, education, household size and composition, and income.

Multistage budgeting, weak separability assumption, and model selection

A three-step multistage budgeting technique was utilized. The first stage involves allocating disposable income over broad categories of food and non-food expenditures. In the second stage, food expenditure is allocated to vegetables and other food commodities. The third stage involves allocating vegetable expenditure across disaggregated vegetable crops commonly consumed in the study area. These were: cowpea (*Vigna unguiculata* L. Walp.) (CP), amaranth (*Amaranthus cruentus* L.) (AM), spider plant (*Cleome gynandra* L.) (SP), African nightshade (*Solanum scabrum* Mill.) (NS), jute mallow (*Corchorus olitorius* L.) (JM), slender leaf (*Crotalaria brevidens* Benth) (SL), cabbage (*Brassica oleracea* L.) (CG), kales (*Brassica oleracea var acephala*) (KL) and spinach (*Spinacia oleracea* L.) (SN). Among these vegetables, CP, AM, SP, NS, JM, and SL are leafy AIV crops, while CG, KL, and SN are exotic vegetables. A stepwise process is convenient in estimating a demand system because only total expenditure on commodities within a sub-category is required (**Phlips, 1974**). The study assumed weak separability of the utility function where the marginal rate of substitution of any two vegetables is independent of quantities of other food commodities consumed outside the vegetable sub-category (**Edgerton, 1997**).

Interdependence in consumer choices necessitates the use of a system approach over a single equation method in estimating commodity demand, since the former permits commodity substitution (**Dudek, 2010; Bett *et al.*, 2012**). Commonly used system approaches include Linear Expenditure Systems (**Stone, 1954**); AIDS (**Deaton and Muellbauer, 1980a**); Generalized Almost Ideal Demand Systems (**Billino, 1990**); and Quadratic Almost Ideal Demand System (**Banks *et al.*, 1997**). Model selection for demand analysis depends on the ease of estimation and ability to generate estimates consistent with demand theory (**Wang *et al.*, 1996**). The current study used the Linear Approximate Almost Ideal Demand System (LA/AIDS) model since its parameters are relatively easy to estimate. It also allows testing for principle restrictions of the demand system. Additionally, axioms of choice are exactly satisfied, and the model is flexible in explaining how income and price variations influence demand responses using data from household expenditure (**Deaton and Muellbauer, 1980a; Lee *et al.*, 1994**).

Empirical derivation of the LA/*AIDS *model

Generating biased parameter estimates was avoided by using the Heckman two-step technique to censor observed zero values of dependent variables, correcting for selectivity bias (**Heckman, 1979; Heien & Wessells, 1990**). In the first stage, a selection equation (Probit model) estimated the probability of consuming each of the selected vegetables (Equation 7).

$$Y_{ih} = f(P_{ih}, P_{(j-1)h}, M_h, X_h) \quad (7)$$

Where: Y_{ih} represents vegetable consumption i by household h ($Y_{ih} = 1$ if vegetable i was consumed, otherwise 0), P_{ih} is the price of vegetable i, $P_{(j-1)h}$ indicates prices for other vegetables, M_h is expenditure (total income allocated) on vegetable consumption, and X_h is a vector of demographic variables explaining household h.

The Probit regression also estimated the Inverse Mills Ratio (IMR) λ_{ith} for a household h in consuming vegetable i (Equation 8).

$$\lambda_{ith} = \frac{\emptyset(P_h,\ M_h,\ X_h)}{\varphi(P_h,\ M_h,\ X_h)} \quad (8)$$

Where P_h is a vector of prices; X_h as explained above; $\emptyset$ is standard normal density function; φ is the standard normal cumulative distribution function. Similarly, IMR for zero consumption of each of the selected vegetables by household h was derived as in Equation (9).

$$\lambda_{ith} = \frac{\emptyset(P_h,\ M_h,\ X_h)}{1-\varphi(P_h,\ M_h,\ X_h)} \quad (9)$$

The IMR for each variety was included as an instrument in the second-stage of the regression to censor latent variables, where a complete demand system (LA/AIDS) was estimated using the Seemingly Unrelated Regression method (**Zellner, 1963**) (Equation 10).

$$\mathrm{W}_i = \alpha_i + \sum_{j=1}^{n} \gamma_{ij}\ \mathrm{In}\, P_j + \beta_i\, \mathrm{In}\left(\frac{m}{P}\right) + \sum_{j=1}^{n} \gamma_{kj} x_k + \beta_{w_i}\lambda_i + \mu_i \quad (10)$$

Where: W_i is the budget share of vegetable i -derived as $\mathrm{W}_i = {(p_i q_i)}/{m}$ in which q_i is the quantity of vegetable i purchased; α_i is a constant coefficient in i^{th} share equation; γ_{ij} is slope coefficient associated with j^{th} good in i^{th} share equation; P_j is the price of the j^{th} commodity; n is number of vegetable crops; x_k are demographic variables which are z in total; λ_i is inverse mills ratio; μ_i is a random variable with zero mean and constant variance; m is the total expenditure on selected vegetables analysed, given as $m = \sum_{j=1}^{n} p_i\, q_1$; and P is the price index for aggregate food provided by Equation (11).

$$\ln(P) = \alpha_0 + \sum_j^n \alpha_i \ \text{In}(P_j) + \frac{1}{2}\sum_j^n \sum_i^n \text{In}(P_i)\text{In}(P_j) \quad (11)$$

It is empirically difficult to derive a price index using Equation (11); hence it was approximated using the Stone Price Index (**Green & Alston, 1990**) as shown in Equation (12).

$$\ln(P) = \sum_i^n \overline{w}\, \text{In}P_i \quad (12)$$

Where: $\overline{w}$ is mean budget share. This process minimizes the effects of multicollinearity, retains linearity in estimation, and enhances the inclusion of demographic variables by either translation or scaling method (**Pollak & Wales, 1981; Sadoulet & de Janvry, 1995**).

Theoretically, the demand system has to satisfy three-parameter requirements. Firstly, the adding up restriction requires equality between the estimated household budget and total expenditure on goods. Secondly, homogeneity restriction implies a proportionate change in expenditure, and prices leave quantity demanded unchanged. Thirdly, symmetry restriction indicates the substitution matrix is symmetric. Thus, cross-price derivatives are negative and semi-definite, implying Hicksian demand function slopes downwards (**Deaton & Muellbauer, 1980b; Varian, 1992; Edgerton, 1997**). These restrictions are satisfied as Equation (13) – Equation (15).

Adding up

$$\begin{Bmatrix} \sum_i^n \alpha_i=0; & \sum_i^n \gamma_{ij}=0; & \sum_i^n \beta_o=0 \\ \sum_i^n w_i=0; & j=1,\ldots\ldots\ldots & \ldots\ldots\ldots\ldots,n \end{Bmatrix} \quad (13)$$

Homogeneity

$$\{\sum_i^n \gamma_{jk} = 0; j = 1, \ldots \ldots \ldots .. n\} \quad (14)$$

Symmetry

$$\{\gamma_{ij} = \gamma_{ji}\} \quad (15)$$

Parameters estimated from LA/AIDS equation form the basis for generating Marshallian and Hicksian elasticities. According to **Green & Alston (1990)** and **Hayes *et al.* (1990)**, Marshallian price and expenditure elasticity estimates are first obtained.

Marshallian expenditure elasticity (Equation 16).

$$e_i = 1 + \left(\frac{1}{\overline{w_i}}\right)\left(\frac{\partial w_i}{\partial \log x}\right) = 1 + \frac{\beta_i}{w_i} \quad (16)$$

Marshallian own-price elasticity (Equation 17).

$$S_{ii}^M = -1 + \left(\frac{\gamma_{ii}}{\overline{w_i}}\right) - \beta_i \quad (17)$$

Marshallian cross-price elasticity (Equation 18).

$$S_{ij}^M = -\delta_{ij} + \left(\frac{\gamma_{ii}}{\overline{w_i}}\right) - \left(\frac{\beta_{ij}}{\overline{w_i}}\right), \forall_i, j = 1, \ldots n \quad (18)$$

Where: δ_{ij} is Kronecker delta in which $\delta_{ij} = 1$ for $1 = j$ (for own-price elasticity), while $\delta_{ij} = 0$ for $1 \neq j$ (for cross-price elasticity). Hicksian elasticities for good i with respect to j are then derived from Marshallian price elasticities using Slutsky equation as Equation (19) – Equation (20).

Hicksian own-price elasticity

$$S_{ii}^M = -1 + \left(\frac{\gamma_{ii}}{\overline{w_i}}\right) - \overline{w_i} \quad (19)$$

Hicksian cross-price elasticity

$$S_{ij}^M = -\delta_{ij} + \left(\frac{\gamma_{ii}}{\overline{w_i}}\right) + \overline{w_i}, \forall_i, j = 1, \ldots n \quad (20)$$

Marginal expenditure shares, which show how future household expenditure on vegetables would be affected by changes in income, were obtained by multiplying expenditure elasticities with expenditure shares allocated to each vegetable crop (**Agbola, 2003; Bett *et al.*, 2012**). Income elasticities are obtained by multiplying expenditure elasticities and coefficient of natural log of T, where T is the total expenditure on food and non-food items. The coefficient of $\ln T$ is derived from Equation (21).

$$\ln R = \alpha_0 + \alpha_1 \ln T + \beta \ln P + \sum_{k=1}^z \gamma_k x_k + \mu \quad (21)$$

Where: R is the total expenditure on vegetable products.

The singularity error in the variance-covariance matrix was avoided by dropping the spinach equation and later recovered by imposing the demand system's adding-up restriction. A similar forum for the LA/AIDS model has been used in other studies to estimate food demand patterns (e.g., **Jabarin & Al-Karableh, 2011; Naanwaab & Yeboah, 2012; Bett *et al.*, 2012; Basarir, 2013**). Demographic variables included in the empirical model (Table 1) are drawn from previous related studies (**Bett *et al.*, 2012; Basarir, 2013; Ogundari & Arifalo, 2013; Ayanwale *et al.*, 2016**).

RESULTS AND DISCUSSION

Descriptive results

Descriptive results on demographic variables are presented in Table 1. The mean age for key decision-makers was about 42 years, with approximately ten years of schooling. The average household size was approximately five family members, with about 27% below 14 years of age. On average, households had 24 years of AIV consumption experience. Moreover, about 64% of respondents were urban dwellers, and nearly 32% of key decision-makers were male.

Weekly consumption, expenditure allocation, and budget share were highest on NS, followed by SP (Table 2). Expenditures on JM, SL, and CG were the least. Expenditure on KL and SN were fairly allocated. About 18.09% of the vegetable budget was allocated on NS, while approximately 5.43% was apportioned on SL share.

Effect of demographics, price and expenditure coefficients on vegetable budget shares

Table 3 shows evaluated maximum likelihood estimates for demographic effects on vegetable budget shares. A significant inverse mills ratio on CP indicates the estimated parameter would be biased and inconsistent if non-consumers of CP were excluded in the analysis. Urban dwellers were less likely to allocate KL and CG budget shares. These results were against study expectations as urban dwellers prefer vegetables that require less preparation time and are more convenient to cook, like KL and CG. Perhaps the ongoing promotional campaigns in urban areas about the importance of leafy

AIVs have enhanced nutritional awareness, thus declining KL and CG preference (**Ngugi *et al.*, 2007**).

Male decision-makers were less likely to allocate AM and JM shares. However, they positively influenced KL share. Perhaps male decision-makers prefer KL since its recipe does not necessarily require blending with other vegetables. Contrary, AM, and JM require mixing with other vegetables to improve their taste and palatability. The implication is that extra time and adequate indigenous knowledge to attach perfect complements is likely a constraint among male decision-makers. More years of education positively influenced the odds of allocating CP, SP, and JM shares and negatively affected CG share. These findings demonstrate that more educated households prefer AIVs to exotic vegetables. Perhaps their higher advancement in knowledge informs their decision to select more nutritious diets.

Large households were more likely to allocate CP and CG shares. CP has about seven seasons per annum (**Mumbi *et al.*, 2006**), an agronomic advantage that enhances its availability, making it more reliable, especially for large households. The market price for CG is relatively lower than other vegetables, improving its affordability in larger families, who require larger quantities of vegetables per meal. Moreover, SL was less preferred in households with most members aged at least 14 years old. Probably, the bitter taste associated with SL makes it an undesirable vegetable, especially when not cooked well (**Abukutsa, 2007**). Contrary, households with more years of AIV consumption were more likely to allocate NS and SL shares. Perhaps more experienced AIV consumers value the bitter taste associated with NS and SL vegetables as an essential medicinal property for healing stomach-related diseases (**Maundu *et al.*, 1999; Schippers, 2002**).

Results in Table 4 shows that the effects of price and expenditure coefficients on vegetable budget shares varied. Apart from JM, own-price coefficients for other vegetable shares were positive. Own-price coefficients were significant for all vegetables except JM and SL, implying that price changes would significantly affect the quantity demanded of CP, AM, SP, NS, KL, and CG. Expenditure coefficients were positively significant for AM, NS, and SL shares, indicating that their purchased quantities would increase upon an increase in real income. Contrary, shares for CP and CG would significantly reduce as a result of the change.

Effect of own-price and cross-price elasticities on vegetable shares

Table 5 presents own and cross-price elasticities results, comprising Marshallian (uncompensated) and Hicksian (compensated) price elasticities. All vegetables considered in this study are normal goods. This explains the concavity of the expenditure function, hence satisfying the negativity of substitution effect on the Hicksian demand curve.

Apart from JM, other uncompensated own-price elasticities of vegetable demand were < 1 in absolute terms thus, inelastic. The implication is that a fall in own prices would lead to a less proportionate increase in quantity demanded of CP, AM, SP, NS, SL, KL, CG, and SN shares.

Table 1: Definition of variables and descriptive statistics

Variable	Variable definition and measurement	Mean	S.E[a]
Age	Age of the decision-maker[b] (years).	41.56	0.698
Educ	Education level of the decision-maker (years).	10.04	0.267
Hsize	Number of members in a household.	4.80	0.123
Hs1	Proportion of household members < 14 years.	0.27	0.013
Hs2	Proportion of the household members ≥14 years.	0.73	0.013
Gender	Proportion of male decision-maker.	0.32	0.027
Exper	Years of AIV consumption in a household.	24.25	0.987
Loc	1 if the household is located in urban areas, 0 otherwise.	0.64	0.028
Lnpid	Real vegetable expenditure.	0.92	0.011
Imr	Inverse mills ratios.		
$P_1, P_2, \ldots, P_9$	Prices for CP, AM, SP, NS, JM, SL, SW, CG and SN vegetables, respectively.		

Note: [a] S.E. = standard error; [b] Decision maker is a household member responsible for key decisions on matters concerning food consumption.

Table 2: Weekly consumption, vegetable expenditure, and budget shares

Type of vegetable	Percent of Consumers	Mean Expenditure (KES[a])	Budget share
Cowpea (CP)	75.40	215.86	0.1648
Amaranthus (AM)	71.90	181.96	0.1265
Spider plant (SP)	76.30	219.51	0.1600
African nightshade (NS)	81.70	256.26	0.1809
Jute mallow (JM)	42.90	82.25	0.0593
Slender leaf (SL)	37.50	83.79	0.0543
Kales (KL)	66.90	130.41	0.1086
Cabbage (CG)	46.70	89.79	0.0717
Spinach (SN)	56.20	106.31	0.0739

Note: [a]1US$ = 102.04 Kenyan Shillings (KES).

Table 3: Effects of demographic variables on vegetable budget shares

Variable	Share of vegetable crops								
	CP	AM	SP	NS	JM	SL	KL	CG	SN
Loc	0.021	-0.002	0.027	-0.006	0.016	0.010	-0.033**	-0.040***	0.007
	(0,019)	(0.013)	(0.019)	(0.017)	(0.011)	(0.011)	(0.016)	(0.013)	
Age	-0.001	0.003	-0.001	0.012	0.001	-0.001	-0.009	0.003	-0.006
	(0.009)	(0.006)	(0.009)	(0.008)	(0.005)	(0.005)	(0.008)	(0.006)	
Gender	0.026	-0.029**	0.008	0.020	-0.019*	-0.010	0.034**	-0.016	-0.014
	(0.019)	(0.013)	(0.019)	(0.017)	(0.011)	(0.011)	(0.016)	(0.013)	
Educ	0.004*	-0.001	0.001***	0.002	0.014**	0.001	-0.005	-0.026*	-0.002
	(0.002)	(0.002)	(0.002)	(0.019)	(0.012)	(0.001)	(0.018)	(0.014)	
Hsize	0.010**	-0.003	0.003	-0.004	-0.004	-0.007	0.004	0.005*	0.002
	(0.005)	(0.003)	(0.002)	(0.004)	(0.006)	(0.004)	(0.008)	(0.003)	
Hs1	0.301	0.081	0.259	-0.151	0.013	-0.040	-0.200	-0.281	0.016
	(0.403)	(0.272)	(0.398)	(0.343)	(0.224)	(0.220)	(0.328)	(0.263)	
Hs2	0.282	0.069	0.238	-0.176	0.031	-0.058*	-0.169	-0.254	0.038
	(0.402)	(0.271)	(0.397)	(0.343)	(0.223)	(0.019)	(0.328)	(0.263)	
Exper	0.001	-0.005	0.003	0.002***	0.005	0.008*	0.003	-0.001	-0.001
	(0.008)	(0.006)	(0.008)	(0.007)	(0.001)	(0.005)	(0.007)	(0.005)	
Imr	-0.041*	0.004	-0.013	0.003	0.016	0.003	0.009	0.020	0.003
	(0.024)	(0.016)	(0.023)	(0.020)	(0.013)	(0.013)	(0.019)	(0.015)	

Note: ***, **, *denotes 1, 5, or 10% level of significance, respectively; values in parentheses indicate standard error.

Table 4: Own and cross-price elasticities for vegetable demand

Shares	CP	AM	SP	NS	JM	SL	KL	CG	SN
Marshallian (uncompensated) price elasticities									
CP	**-0.864**	0.087	0.240	0.909	-0.678	-1.897	0.174	2.677	0.149
AM	1.076	**-0.211**	-0.946	-0.865	-0.791	-1.815	0.096	2.883	0.141
SP	1.065	-1.061	**-0.677**	0.856	0.969	-2.023	0.520	2.526	0.322
NS	1.265	-0.728	0.244	**-0.920**	-1.277	-1.895	0.092	2.898	0.049
JM	-1.361	-1.216	0.162	-1.115	**-1.506**	-1.562	0.108	2.967	0.077
SL	-0.769	-1.218	-0.143	-1.503	-1.047	**-0.833**	0.243	2.366	0.453
KL	1.125	1.752	0.136	1.776	1.269	2.239	**-0.845**	2.742	-1.086
CG	2.066	0.046	1.198	0.013	0.195	0.849	0.723	**-0.585**	1.062
SN	1.210	0.882	0.393	0.949	0.812	1.800	-0.202	2.805	**-0.744**
Hicksian (compensated) price elasticities									
CP	**-0.500**	0.163	0.036	0.208	-0.087	-0.100	0.020	0.275	0.057
AM	0.161	**-0.196**	-0.006	-0.221	-0.194	-0.042	0.136	0.056	0.092
SP	0.030	-0.032	**-0.454**	0.265	0.080	-0.039	0.215	0.150	0.100
NS	0.020	-0.052	0.005	**-0.911**	-0.098	-0.169	0.210	0.207	0.079
JM	-0.230	-0.281	0.011	-0.197	**-1.495**	-0.041	0.219	0.165	0.192
SL	-0.316	-0.207	-0.071	-0.015	-0.008	**-0.877**	0.418	0.234	0.164
KL	0.276	0.209	0.091	0.373	0.175	0.104	**-0.759**	0.367	-0.212
CG	0.079	0.743	0.369	0.646	0.398	0.384	0.644	**-0.323**	0.845
SN	1.021	0.963	0.965	1.117	1.066	1.006	-1.034	0.612	**-0.682**

Note: The bold values are the own-price elasticities.

Table 5: Marginal shares, income and expenditure elasticities for vegetable demand

CP	AM	SP	NS	JM	SL	KL	CG	SN
Marginal expenditure shares								
0.035	0.238	0.097	0.353	0.108	0.152	0.131	-0.129	0.086
Expenditure elasticities								
0.210	1.882	0.607	1.949	1.812	2.800	1.202	-1.805	1.167
Income elasticities								
0.144	1.291	0.416	1.337	1.243	1.921	0.824	-1.238	0.800

Table 6: Effect of price and expenditure coefficients on vegetable budget shares

Prices	Shares of vegetable varieties								
	CP	AM	SP	NS	JM	SL	SW	CG	SN
P1	0.045*	-0.048***	-0.033*	0.004	0.004	0.007	-0.015	0.033***	-0.003
	(0.026)	(0.014)	(0.019)	(0.017)	(0.013)	(0.013)	(0.015)	(0.012)	
P2	-0.048***	0.116***	-0.026*	-0.002	0.010	-0.019	-0.003	-0.023**	-0.005
	(0.015)	(0.018)	(0.014)	(0.014)	(0.012)	(0.012)	(0.012)	(0.009)	
P3	-0.033*	-0.026*	0.077***	0.002	-0.008	-0.014	0.006	0.001	-0.007
	(0.019)	(0.014)	(0.024)	(0.016)	(0.013)	(0.013)	(0.015)	(0.011)	
P4	0.004	-0.002	0.002	0.047**	0.002	-0.010	-0.027**	-0.020*	0.003
	(0.017)	(0.014)	(0.016)	(0.021)	(0.012)	(0.012)	(0.013)	(0.010)	
P5	0.004	0.010	-0.008	0.002	-0.027	-0.005	0.008	0.007	0.008
	(0.013)	(0.012)	(0.013)	(0.012)	(0.019)	(0.015)	(0.012)	(0.008)	
P6	0.007	-0.019	-0.014	-0.010	-0.005	0.012	0.016	0.008	0.004
	(0.013)	(0.012)	(0.013)	(0.012)	(0.015)	(0.018)	(0.011)	(0.008)	
P7	-0.015	-0.003	0.006	-0.027**	0.008	0.016	0.029*	-0.015	0.002
	(0.015)	(0.012)	(0.015)	(0.013)	(0.012)	(0.011)	(0.017)	(0.009)	
P8	0.033***	-0.023**	0.001	-0.020**	0.007	0.008	-0.015	0.035***	-0.027
	(0.012)	(0.009)	(0.011)	(0.010)	(0.008)	(0.008)	(0.009)	(0.001)	
P9	-0.003	-0.005	-0.007	0.003	0.008	0.004	0.002	-0.027***	0.024
	(0.013)	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.008)	
Constant	-0.002	-0.054	-0.069	0.169	0.018	-0.017	0.304	0.549**	-0.898
	(0.399)	(0.269)	(0.394)	(0.341)	(0.222)	(0.218)	(0.326)	(0.261)	
Lnpid (β_{ij})	-0.199***	0.112***	-0.063	0.172***	0.048	0.098***	0.022	-0.201***	0.012
	(0.056)	(0.039)	(0.055)	(0.048)	(0.033)	(0.032)	(0.045)	(0.039)	

Note: ***, ** and *represents significance at 1%, 5% and 10% level, respectively.
Values in parenthesis indicates the standard errors.

More income would be allocated to AM share if all vegetable prices increased uniformly. However, a uniform decrease in vegetable price would significantly favour JM share. Similar findings on JM were obtained by **Jabarin and Al-Karablieh (2011)**.

All compensated own-price elasticities were also negative, confirming the downward sloping of the Hicksian demand curve with asymmetric, non-positive semi-definite substitution matrix (**Varian, 1992**). Like Marshallian own-price elasticities, Hicksian own-price elasticities of vegetable demand were < 1 in absolute terms, except for JM. An indication that apart from JM, quantities demanded of other shares would not change significantly even if their respective prices changed.

Marshallian and Hicksian price elasticities had similar signs implying that both income and substitution effects would contribute proportionate weights in influencing vegetable purchases for any price change. Compared to uncompensated own-price elasticities, the magnitude of compensated own-price elasticities was higher, indicating that price effect would contribute a more significant proportion of increased demand than income effect in the case of a price decline. Uncompensated own-price elasticity for CP, as an example, implies a 10% drop in CP price would stimulate its demand by 8.6%, where the price effect contributes about 5.0% (compensated own-price elasticity). In comparison, approximately 3.6% would be accounted for by income effect.

Negative Marshallian and Hicksian cross-price elasticities imply the respective vegetable pairs are complimentary, otherwise substitutes. Out of 30 cross-price elasticities among leafy AIV crops, 20 were negative while 10 were positive, indicating leafy AIVs complement each other in consumption than they substitute. For instance, holding price for AM and JM constant, if the price for CP increases by 10%, quantity demanded of AM increases by 0.87%, with pure price accounting for 16.3% of the increased demand. Similarly, the amount demanded of JM would decline by 6.78% as a result of the change. Generally, leafy AIV crops were substitutes for exotic vegetables. Among exotic vegetables, CG substitutes KL and SN, which were also found to be complementary products.

Effect of marginal shares, income and expenditure elasticities on vegetable demand

Results on marginal expenditure shares, income, and expenditure elasticities are presented in Table 6. Marginal expenditure shares for all vegetable sum to one, satisfying the adding up the restriction of the demand system. Apart from CG, other marginal expenditure shares were positive, implying that a future increase in household income would proportionately increase their purchases. As a result, NS would receive the highest (about 35%) proportionate increase in quantity purchased while SN the least (about 9%). Contrary, consumption of CG would proportionately decline due to its negative marginal expenditure share.

Similarly, apart from CG, expenditure and income elasticities for other vegetables were positive, implying normal goods, with elastic income elasticity of demand. Of the nine vegetable crops evaluated, only CP and SP had expenditure elasticities < 1; thus, they can be considered necessary to the household diet. Likewise, AM, NS, JM, SL, KL, and SN can be classified as luxury vegetables since their expenditure elasticities were > 1.

CONCLUSIONS AND RECOMMENDATIONS

The largest proportion of the vegetable budget was allocated on NS, while SL received the slightest share. Shares of different vegetables were significantly influenced by the decision-makers' household location, gender, and education level, household size, composition, and AIV consumption experience. The similarity between compensated and uncompensated price elasticities shows that income and substitution effects proportionately influence vegetable purchases due to price changes. Own-price elasticities indicate that all analysed vegetables are normal products. Hence a uniform increase in price would decrease the quantity demanded. Cross-price elasticities suggest leafy AIV crops are more complementary to each other. However, they are absolute substitutes for exotic vegetables. From expenditure elasticity results, CP and SP can be classified as necessary vegetables due to their less responsiveness to changes in income, probably because they are bought more regularly and in reasonably constant amounts. Likewise, AM, NS, JM, SL, SW, and SN are considered luxury vegetables to the household diet.

Findings from this study have policy implications on food accessibility, which is one of the elements of food security. Even though a future increase in income would proportionately increase vegetable purchases, the magnitude of the price effect outweighs that of the income effect. The implication is that policies favouring the general increase in household income would not significantly increase vegetable demand instead of price regulations. Thus, consumers would purchase more AIVs if price policies were favourable. In this regard, two commentary interventions are proposed; subsidization of farm inputs, remarkably certified seeds to reduce production costs, followed by a price ceiling that could protect and motivate AIV purchases, especially in large households.

Moreover, eliminating brokers from the vegetable value chain could reduce the retail price in favour of consumers. Additionally, utilization of leafy AIVs for health purposes was confirmed by more experienced consumers. Therefore, demand for leafy AIV crops could increase by designing educational programs to improve consumer awareness of their medicinal and nutritional benefits, especially in male decision-makers.

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PROFIT EFFICIENCY OF SMALLHOLDER MAIZE FARMERS IN SAGNARIGU MUNICIPAL OF NORTHERN GHANA

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ABSTRACT

Research background: Maize is the most important cereal crop produced by most households in Ghana for income and household food security. Despite its economic importance, not much study has been carried out on maize profit efficiency in Ghana, hence this study.
Purpose of the article: This study estimated profit efficiency of maize farmers in the Sagnarigu municipal of Ghana to understand producers' profit efficiency level and its determinants as well as the challenges faced by maize producers.
Methods: Data was sourced from small-scale maize producers while stochastic frontier analysis was applied to estimate a Cobb-Douglas profit function that simultaneously identified the sources of inefficiency. Kendall's coefficient of concordance was used to analyse the constraints facing maize producers.
Findings, Value added & Novelty: The findings indicated that maize farmers produced at 71% profit efficiency. This is one of very few studies on profit efficiency of Ghanaian maize farmers. The result means that 29% of the achievable maximum profit was forfeited as a result of production inefficiency. Educational attainment and access to agricultural extension service decreased the level of profit inefficiency while age, herd ownership and membership of farmer organization increased profit inefficiency level of farmers. The most critical challenges reported by farmers were financial constraints, high cost of ploughing and difficulty in acquiring chemical fertilizer. The study recommends that access to agricultural extension service should be improved to cover more farmers while efforts should be made to expand educational access in rural areas to enhance the profit efficiency of farmers.

Keywords: profit efficiency; maize; stochastic frontier analysis; smallholder farmers; Ghana
JEL Codes: C21; D24; Q12

INTRODUCTION

The multi-dimensional role of agriculture in reducing hunger and poverty under the Sustainable Development Goals (SDGs) is well acknowledged. The agricultural sector in Africa is estimated to play a key role in poverty reduction (**Christiaensen *et al.*, 2011**). Small-scale farming accounts for over 90 per cent of the economically active rural population of Ghana (**Ghana Statistical Service, 2014**). Farmers involved in small-scale agriculture have limited access to assets that facilitate the transition from less productive farming to modern commercial farming. Compared to other countries worldwide in terms of agricultural productivity, Ghana still lags behind (**Fuglie & Rada, 2013**).

Invariably, certain obstacles exist that prevent Ghana's agricultural sector from realising its full potential. Studies have shown that inefficiencies and significant yield gaps exist in small-scale farming in several developing countries (**Anang *et al.*, 2016; Abdulai et *al.*, 2013; Al-hassan, 2012).** These inefficiencies are related to factors such as low adoption of improved technologies, lack of access to farm inputs and services, poor technical knowhow, environmental factors, among others.

Improving the profitability of farming particularly among smallholder farmers is a very important goal for most developing countries because majority of the population in these countries are engaged in farming as a source of livelihood. Farm households are involved in agricultural production with the aim of achieving household livelihood goals such as food and income security. Farmers operate in a competitive environment and must therefore combine resources in a judicious manner to ensure that they achieve optimum levels of production and profit from farming.

The goal of profit maximization may not be explicitly stated by smallholders, nevertheless, any production system that is not profitable may not be sustainable over time. Enhancing the level of profitability requires technical skills in producing optimally and eliminating waste. It also relates to right combination of inputs taking into consideration the input price levels. Thus, profitability can be influenced by managerial as well as institutional and marketing factors. Factor prices and capability in allocating these resources are essential to raise profitability of smallholder farmers.

Maize is an important staple food and cash crop produced by most smallholder farmers in Ghana. The crop is produced by most farm households as it forms an important part of the diet of Ghanaians and brings considerable income to producers. Maize production is however not without challenges, especially with regards to acquisition of external inputs such as chemical fertilizers, cost of land preparation, unavailability of improved seeds and pest and disease challenges. These challenges affect the profitability of maize production and the total area farmers are likely to put under cultivation. This study therefore explores the profit efficiency of small-scale maize farmers in the Sagnarigu municipal of Ghana to highlight the sources of inefficiency as well as the critical challenges confronting farmers.

There are not many studies focusing on profit efficiency of maize production in Ghana which warrants this study. A search through the literature reveals that there is paucity of research on profitability and profit efficiency of maize cultivation in Ghana and particularly the study area. This is against the backdrop that maize is the most widely cultivated and consumed cereal crop in Ghana, and plays a very crucial role in household food and income security. The few studies that have examined maize profit efficiency in Ghana have shown varied results and include **Wongnaa *et al. (2019)***, **Ansah *et al. (2014)*,** and **Bidzakin *et al.* (2014).** The study by **Wongnaa *et al*. (2019)** focused on four ecological zones of Ghana and estimated the mean profit efficiency at 48.4%, while **Ansah *et al.* (2014)** focused their study on the forest belt of Ghana and reported a mean profit efficiency of 89**%. Bidzakin *et al.* (2014)** undertook their study in northern Ghana and reported a mean profit efficiency of 61%. Clearly, the results are quite inconclusive regarding the level of profit efficiency among Ghanaian maize farmers. The scarcity of research in this area of study means that there exist inadequate research findings necessary to enhance maize profit efficiency and profitability across the country. This study therefore contributes to the body of knowledge on maize profit efficiency of peasant farmers and fills an important research gap.

LITERATURE REVIEW

According to **Konja *et al.* (2019)**, agriculture is key to economic development in Ghana, hence the need to pay attention to output and productivity growth. Resource constraints, high cost of farm inputs, use of rudimentary equipment in farming among others contribute to low farm profits in many developing countries. Most farms in Ghana and other developing countries remain small with little investment of capital to increase farm profits. Increasing the profitability of smallholder farmers therefore remains a critical challenge confronting policymakers and researchers.

Agriculture in sub-Saharan Africa is dominated by food crop production (**Mujuru *et al.*, 2022**), with crop farming contributing immensely to rural development, income and food security and rural livelihoods (**Khoza *et al.*, 2019**). Maize is an important food crop produced in most parts of Africa, notably among farm households and is the main dietary staple in Ghana and several African countries. The profitability of maize production hinges very much on conditions in the input and output markets (**Mujuru *et al.*, 2022**), as well as farm and farmer characteristics that influence the level of productivity. Farmers' ability to reduce inefficiency in production and optimise resource-use efficiency are necessary to improve productivity and profitability of maize production.

Profit efficiency connotes the ability of farmers to produce at the highest possible profit taking into account input prices and the level of fixed production inputs (**Ali & Flinn, 1989; Rahman, 2003).** It entails producers' ability to produce on the profit frontier while any deviations from the frontier are construed as inefficiency of production. In profit efficiency analysis, producers are regarded as profit-maximisers, as opposed to cost-minimisers (where output level is regarded as exogenously given). Output and inputs are decided by the producer, with the objective of maximizing profits.

Measurement of efficiency typically follows a parametric or non-parametric approach. The parametric approach is centred on econometric estimation of a production frontier. The approach is made up of the stochastic frontier and deterministic frontier models. The parametric frontier methods impose a functional form on the production function based on assumptions made about the data. The commonly used functional forms consist of the Cobb–Douglas, constant elasticity of substitution, and translog production functions. The parametric approaches are divided into deterministic frontiers and stochastic frontiers. A deterministic frontier is based on the assumption that all deviations from the production or cost frontier are as a result of inefficiency of firms/farmers. Conversely, stochastic frontiers assume that a portion of the discrepancies from the frontier is as a result of random noise such as measurement error and statistical noise and also partially as a result of firm-specific inefficiency (**Forsund *et al.*, 1980; Coelli *et al.*, 2002).** The stochastic frontier approach tries to differentiate effects of random noises from the effects of inefficiency. As a result, it has the strength of testing statistical hypothesis over the deterministic frontier.

The application of the non-parametric approach in efficiency analysis includes the free disposal hull (FDH) and the data envelopment analysis (DEA), with DEA being the most popular non-parametric method. DEA was first initiated by **Farrell (1957)** and introduced into modern economic literature by **Charnes *et al.* (1978)** while FDH was developed by **Deprins *et al.* (1984).** DEA is used to analyse production, cost and revenue and profit data without technology parameterization (Greene, 2008). It does not impose a functional form on the production and cost frontier nor make any assumptions about the distribution of the error term. DEA uses either an input or output orientation to measure efficiency, based on whether the producer has more control over inputs or output level. The efficiency frontier in DEA stems from the concept of Pareto optimality; a firm may increase (decrease) output without necessarily increasing (decreasing) production of another product. DMUs on the frontier are considered as Pareto optimal units and are assigned an efficiency score of one (fully efficient). DMUs that are not on the efficient frontier are considered to be relatively inefficient and are given a positive efficiency index of less than one **(Chimai, 2011).**

While there are also semi-parametric techniques in assessing efficiency, these techniques have not gained much prominence in the literature. Semi-parametric techniques are statistical models that have parametric and nonparametric components; a finite-dimensional component and an infinite-dimensional component. Semi-parametric techniques include productivity indices, growth accounting, index theory, and many others.

DATA AND METHODS

The study area and sampling procedure

The research was carried in the Sagnarigu municipality of the Northern Region of Ghana. The municipality is located in the Guinea savanna and covers 200.4 km² of land with a population of 148,099 (**Ghana Statistical Service, 2010).** It has a single rainfall regime and a long dry spell during the dry season. The area experiences high annual temperatures during the dry season (up to about 40 degrees Celsius) and dry harmattan winds. The economy of the municipality is mainly agriculture and commerce-based. The cultivation of maize, rice, and soybean is a major activity in the municipality.

The research involved primary data collection from smallholder farm households in the area. Multistage random sampling was used in the data collection. Sagnarigu municipal was first chosen within the northern savanna as a major maize producing area. This was followed by random sampling of six maize producing communities in the municipality. Thereafter, simple random sampling was applied to select thirty respondents per community to provide a total of 180 respondents. The respondents were interviewed using a semi-structured questionnaire with the interviews conducted in the local dialect since most of the respondents could not read and write. One respondent was dropped from the analysis due to incomplete information. The data covered activities for the 2018/2019 cropping season.

Efficiency concepts and measurement

Efficiency measurement was introduced by **Farrell (1957**) and described by **Kumar & Gulati (2010)** as a measure of operational excellence in the resource utilization process. Closely related to efficiency is productivity. Productivity in its simplest form is determined by dividing the output realised by the total physical inputs or resources (land, labour, seed, etc.) utilised in production. In other words, productivity is simply efficiency in production (**Syverson, 2011**). Single-factor productivity also measures or reflects units of output produced per unit of a particular input. A firm is said to be inefficient when it does not attain to the potential maximum output.

A firm in the production process is likely to experience some components of productive efficiency, namely: technical, allocative and economic efficiencies. Discrepancies in output between farmers can be explained by the differences in efficiency. Thus, the production frontier describes the highest attainable output given the minimum inputs needed to obtain a particular output. In other words, for each input mix the production frontier depicts the maximum attainable output. Technical inefficiency denotes failure of the farmer or firm to attain the frontier level of output, given the level of inputs (**Kumbhakar, 1994**). Consequently, inefficiency arises when the observed output lies below the frontier. Allocative efficiency is a firm or farmer's ability to use inputs in their optimal way, given their respective prices (**Uri, 2001**). If a farmer fails in allocating inputs at minimized cost, given the relative input prices, then there is allocative inefficiency or resource misallocation. The implication is that, misallocating resources will result in increased cost of production and hence decreased profit. Again, if the marginal rate of technical substitution between any two inputs is not equal to the resulting proportion of factor prices, a firm or farmer is said to be allocatively inefficient. This could be due to sluggish adjustment to price changes and regulatory challenges (**Atkinson & Cornwell, 1994**). In the production process, a firm may be technically efficient but allocatively inefficient, allocatively efficient but technically inefficient, both technically and allocatively efficient, and at worse, technically and allocatively inefficient. Economic efficiency seeks to pool technical and allocative efficiencies to depict the ability of a firm or farmer to produce at possible minimum cost, given input price and a set of inputs. Consequently, achieving technical or allocative efficiency is only a necessary but not a sufficient condition for economic efficiency. A firm or farmer must at the same time achieve both technical and allocative efficiencies if it is to achieve economic efficiency.

Stochastic profit frontier model

The stochastic profit frontier function is modelled based on **Battese & Coelli (1995)** as Equation (1).

$$\pi_i = f(P_i, Z_i)\, exp(e_i)\, ; \quad e_i = v_i - u_i \tag{1}$$

Where: π_i is normalized profit, P_i is normalized input price, Z_i denotes the level of a fixed inputs, and e_i represents the composed error term. v_i is random errors beyond the producer's control while u_i denotes factors within the farmer's control.

The inefficiency effects (u_i) is modelled as Equation (2).

$$u_i = \delta_0 + \sum_{k=1}^{n} \delta_k W_{di} + \varepsilon_i \tag{2}$$

Where: W_{di} represents the factors associated with inefficiency, ε_i is random error and δ_0 and δ_k are unknown parameters.

Profit efficiency is obtained as the ratio of the observed profit to the frontier profit (**Aigner *et al.*, 1977**; **Meeusen & Van den Broeck, 1977)** (Equation 3 – Equation 6).

$$\pi_e = \frac{\pi_i}{\pi_{max}} \tag{3}$$

$$\pi_e = \frac{f(P_{ij}, X_{ij}, \beta_i).exp(v_i - u_i)}{f(P_{ij}, X_{ij}, \beta_i).exp(v_i)} \quad (4)$$

$$\pi_e = exp(-u_i) \quad (5)$$

$$\text{Profit inefficiency} = 1 - \pi_e \quad (6)$$

Where: π_e is profit efficiency, π_i is observed profit, and π_{max} is the frontier profit.

The study adopted the Cobb-Douglas functional form for the analysis. The empirical Cobb-Douglas stochastic profit frontier model can be expressed as Equation (7).

$$ln\pi_i = \beta_0 + \beta_1 lnx_{1i} + \beta_2 lnx_{2i} + \beta_3 lnx_{3i} + \beta_4 lnx_{4i} + \beta_5 lnx_{5i} + \beta_5 lnx_{6i} + \beta_5 lnx_{7i} + v_i - u_i \quad (7)$$

The x_i variables include both conventional inputs and fixed production inputs used in the cultivation of rice. The variables included unit price of seed, labour, fertilizer, herbicide, ploughing cost per acre as well as the size of land and amount of capital used in production.

The inefficiency model is given as Equation (8).

$$u_i = \delta_o + \delta_1 z_{1i} + \delta_2 z_{2i} + \delta_3 z_{3i} + \delta_4 z_{4i} + \delta_5 z_{5i} + \ldots\ldots\ldots + \delta_n z_{ni} \quad (8)$$

The z_i variables include individual, household, farm and institutional factors identified in the literature to affect profit efficiency.

Descriptive statistics of the respondents

The variables used in the study are described in Table 1 which reveals that the farmers are within the economically active age for farming. A youthful farming population is likely to be more willing to explore new technologies to enhance productivity and profitability. It was also revealed that only 25% of the respondents are educated which could be a drawback to information seeking and technology adoption. On the average, the respondents owned farms with an average size of 3.4 acres suggesting that they are small-scale producers. The study further indicated that most (70%) of the respondents belonged to a farmer-based organization. Thus, new technology or innovation aimed at increasing output and profit could be channel through these organizations to farmers. Also, it was found that most (84%) of the farmers owned cattle, which play a useful role in farming in most rural settings, where they are used to cart goods and plough fields to reduce drudgery associated with farming.

RESULTS AND DISCUSSION

Maximum likelihood estimates of the stochastic frontier profit function

The results in Table 2 show the stochastic profit frontier estimates. The dependent variable, profit, and the input variables were all mean-corrected to zero and log-transformed, implying that the first-order coefficients denote the corresponding elasticities. The results show a good fit of the data as indicated by the significance of the variance parameters. The results show that 61% of the variation in profit is associated with factors within the control of farmers.

The price of labour is positive and significant at 5%, implying that an increase in the average price of labour services increases farm profit. However, the positive effect of labour in this study is at variance with **Amesimeku & Anang (2021)** in their study in northern Ghana. Seed price was also found to be significant at 10% and negatively correlated with profit, revealing that an increase in seed price results in reduction in farm profit. The negative effect of seed price disagrees with **Amesimeku & Anang (2021)** who reported a positively significant effect of seed price on profit of soybean farmers in Ghana. Fertilizer application was found to be significant at 1%, implying an increase in fertilizer price positively correlates with profit of maize farmers. Price of herbicide was found to be significantly related to profit at 10% while the value of farm capital and cultivated land area were both significantly related to profit 1%.

Table 1: Descriptive statistics of the variables

Variable	Measurement	Mean	Std. Dev.	Min.	Max.
Profit	Ghana cedi (GH¢)	1196	879.7	90	5000
Maize price	Ghana cedi/kg	0.997	0.018	0.9	1
Labour price	Ghana cedi/man-day	10.61	1.852	7	15
Seed price	Ghana cedi/kg	1.530	0.706	1	3
Fertilizer price	Ghana cedi/kg	1.267	0.710	0	2.4
Herbicide price	Ghana cedi/litre	14.94	9.815	0	25
Ploughing cost	Ghana cedi/acre	72.01	7.505	45	100
Farm capital	Ghana cedi	297.3	180.4	62	1402
Farm size	Acreage	3.402	2.241	0.5	14
Age	Number of years	42.50	11.64	24	77
Education	Number of years	2.229	4.435	0	16
Owned cattle	1 if yes; 0 otherwise	0.838	0.369	0	1
Extension visits	1 if visited; 0 otherwise	0.447	0.499	0	1
Farmer group	1 if member; 0 otherwise	0.704	0.458	0	1
Fertility of soil	1 if fertile; 0 otherwise	0.330	0.471	0	1

Note: 1 Ghana cedi = USD 0.19. Source: Authors' computation, 2020.

This indicates that an increase in herbicide price, capital and cultivated land area increases farm profit. The positive influence of capital is consistent with the result of **Chikobola (2016)** which indicated a positive effect of farm capital on the profit level of groundnut production in Zambia.

Distribution of profit efficiency scores of maize farmers

The results in Table 3 show the distribution of the profit efficiency scores of the respondents. The producers recorded an average profit efficiency of 71.3%, with a range of 18.2% and 94.2%. This implies that the farmers lose about 28.7% of the profit due to inefficiency. Hence, the farmers could potentially increase profit efficiency by 28.7%.

Most (62.1%) of the farmers had profit efficiency above 70% while very few (14.6%) had profit efficiency up to 50%. Generally, most of the farmers are profit oriented and achieve more than 50% of profit efficiency. This technically allows farmers to be in production, since they are able to meet their average cost of production. On the contrary, farmers' inability to attain 100% profit efficiency could be attributed to limited usage of the available technology for maize production and external shocks such as poor environmental conditions that affect farmers' productivity.

Identifying the sources of profit inefficiency

Table 4 shows the determinants of profit efficiency. Six variables were found to influence profit efficiency either positively or negatively at various significant levels.

Age is positive and significant at 5% implying that an increase in age increases profit inefficiency of maize farmers in the Sagnarigu municipality. This finding is in line **Setsoafia *et al.* (2017)** who found that older artisanal fishers in Pru district of Ghana were less profit efficient as opposed to the younger counterparts. Younger farmers may be more adventurous in terms of adopting new technologies thereby improving their efficiency of production.

Education was measured as a continues variable and was found to positively influence profit efficiency (or negatively influence profit inefficiency) at 10%. This shows that a yearly increase in one's educational level increases the chances of enhancing profit efficiency. This could be due to the influence of education in exposing farmers to modern technologies through knowledge seeking. Farmers who can read and write are more likely to be aware of productivity-enhancing technologies and their correct application. They are also more likely to take advantage of opportunities that improve the lot of farmers such as participation in formal credit market and training programmes, among others. The finding concurs with **Wongnaa *et al.* (2019**) who observed that education correlated positively with profit efficiency of maize farmers in Ghana.

Farmers' access to agricultural extension was significant and negative in relation to profit inefficiency. This shows that access to extension services reduces profit inefficiency (in other words, it enhances profit efficiency). The result agrees with **Amesimeku & Anang (2021)** as well as **Konja *et al.* (2019)** in separate studies with smallholders in northern Ghana. Extension agents are important in smallholder production because they offer technical advice to farmers which contribute to higher productivity and profitability. Extension agents provide a link between farmers and researchers and their role in educating and training farmers on modern production practices to enhance yield and profitability cannot be overemphasized.

Herd ownership and farmer-based organization membership were also significant and positive in relation to profit inefficiency, implying that profit efficiency decreases with herd ownership and farmer-based organization (FBO) membership, which is contrary to expectation. This is because FBOs are expected to serve as a platform for technology adoption and farmer education, thus belonging to a farmer group is anticipated to enhance producers' knowledge about new technologies and their adoption strategies which could directly or indirectly influence profit efficiency. Thus, the FBOs in this study may not be actively engaged in carrying out their core duties or there may be issues of free-riding by some members, thus reducing their effectiveness.

Table 2: Stochastic frontier estimates of the profit function for maize farmers

Variable	Parameter	Estimate	Std. Error
Constant	β_0	0.949	1.691
Labour price	β_1	0.491**	0.192
Seed price	β_2	– 0.149*	0.080
Fertilizer price	β_3	0.062***	0.011
Herbicide price	β_4	0.012*	0.007
Unit cost of ploughing	β_5	0.350	0.335
Capital	β_6	0.593***	0.161
Farm size	β_7	0.421***	0.126
Variance parameters			
Gamma: $\gamma = \sigma_u^2/(\sigma_u^2 + \sigma_v^2)$	γ	0.606***	0.015
Sigma squared: $\sigma^2 = \sigma_u^2 + \sigma_v^2$	σ^2	0.403***	0.018
Log-likelihood	L	– 92.58	

Note: ***, **, and * denote significance at 1%, 5% and 10% level, respectively. Source: Authors' computation, 2020.

Table 3: Distribution of profit efficiency scores

Efficiency range	Frequency	Percent
0.00 – 0.10	0	0
0.11 – 0.20	1	0.6
0.21 – 0.30	3	1.7
0.31 – 0.40	8	4.5
0.41 – 0.50	14	7.8
0.51 – 0.60	12	6.7
0.61 – 0.70	30	16.8
0.71 – 0.80	44	24.6
0.81 – 0.90	61	34.1
0.91 – 1.00	6	3.4
Mean	0.713	
Minimum	0.182	
Maximum	0.942	

Source: Authors' computation, 2020.

Table 4: Determinants of profit inefficiency

Variable	Parameter	Estimate	Std. Error
Constant	α_0	– 3.982**	1.640
Age	α_1	0.036**	0.018
Years of education	α_2	– 0.311*	0.183
Years of education squared	α_3	0.020	0.015
Herd ownership	α_4	1.241**	0.615
Extension visits	α_5	– 0.720*	0.431
Farmer-based association	α_6	0.934*	0.541
Soil fertility status	α_7	– 1.117**	0.481

Note: ***, **, and * indicate significance at 1%, 5% and 10% level, respectively. Source: Authors' computation, 2020.

Table 5: Ranking of constraints facing maize farmers

Variable	Mean score	Std. Dev.	Rank
Financial constraints	2.40	1.84	1st
High cost of ploughing	3.22	2.42	2nd
Difficulty in acquiring fertilizer	4.22	3.56	3rd
Pest and diseases	4.69	2.34	4th
Poor soils	5.73	1.99	5th
Low yields	6.32	1.93	6th
Cost of chemicals for weed control	6.53	3.67	7th
Lack of ready market	7.18	2.05	8th
Low maize price	7.94	1.58	9th
High cost of seeds	8.63	1.87	10th
Unavailability of improved varieties	9.01	2.16	11th

Source: Authors' computation from field survey, 2020.

Soil fertility status was found to negatively influence maize farmers profit inefficiency in the Sagnarigu Municipality. The result implies that producers with fertile land achieve higher profit efficiency relative to producers with infertile land. The reason could be that farmers with fertile soils need fewer external inputs to improve the level of soil fertility thereby reducing production costs and increasing the profitability of farming. Farmers with infertile soils need to apply more external inputs to improve soil fertility which is expected to increase the cost of production and thereby negatively impact on profitability and profit efficiency.

Ranking of constraints faced by maize farmers

Eleven major constraints were identified and ranked as shown in Table 5. The problem with the least mean rank was identified as the most serious constraint and vice versa. Farmers identified financial constraints as the topmost problem affecting their production activities. Smallholder farmers usually find it difficult to access credit from both formal and informal sources. Thus, access to finance remains a critical challenge that confronts Ghanaian smallholder farmers. Smallholders are also generally resource-poor, which affects their access to production inputs. This result is buttressed by findings of **Dimitri & Richman (2000)** and **Garcıa-Gil *et al.* (2000)** which revealed that financing is the main challenge faced by farmers. **Amesimeku & Anang (2021)** reported similar finding in a study in northern Ghana involving smallholder soybean farmers.

The next constraint in terms of importance to the respondents is high cost of ploughing. Usually, farmers depend on commercial tractor operators who live within their communities or nearby villages. However, due to the limited number of such operators, the demand for tractor services always outstrips the supply, driving up prices.

The provision of mechanization centres at the community level is necessary to promote access to tractor services. The study's finding resonates with **Amesimeku and Anang (2021**) who reported high cost of ploughing as the second most important constraint among soybean farmers in northern Ghana.

Farmers identified difficulty in acquiring fertilizer as a major constraint in maize production. Maize is a heavy feeder when it comes to fertilizers and the soils in northern Ghana are generally low in fertility. Lack of access to chemical fertilizer is therefore a major challenge to farmers whose livelihoods depend on crop production. Hence, measures are required to improve farmers' access to chemical fertilizer. This could be done by ensuring efficiency and transparency in the distribution of subsidized fertilizer under the Planting for Food and Jobs (PFJs) initiative of the Government of Ghana. There is also the need to provide incentives and an effective regulative framework to ensure that private input dealers supply farmers with chemical fertilizer and other production inputs at their door steps and at approved prices.

Issues of pests and diseases have become critical in recent times as a result of the emergence of the fall army worm and other pests that devastate the farms of farmers in Ghana. This drives up the cost of chemical pest control which affects profitability of farming. Poor soils were reported as the fifth constraint; poorer soils lead to higher input use with less return. This is closely related to low yields, which was reported as the sixth constraint. Other constraints included the cost of chemical control of weeds, lack of ready market for farm produce, low produce price, high cost of seeds and the unavailability of improved varieties. Adoption of improved seeds is below expectation as many smallholders still cultivate traditional varieties. It is often argued that farmers choose traditional varieties as a risk management tool, since these traditional varieties are better adapted to the local environment and require fewer external inputs, although they give fewer yields. Thus, resource-poor farmers who lack access to credit are more likely to choose local varieties that give minimum yield with minimum external inputs. The challenge is to facilitate smallholders' access to input subsidies to promote adoption of improved varieties to enhance farm yields and profitability.

CONCLUSION AND RECOMMENDATIONS

The study assessed profit efficiency of small-scale maize producers in Sagnarigu municipal of Ghana using stochastic profit function approach. The results indicated that 29% of the potential profit was lost as a result of production inefficiency of farmers. Educational attainment and access to agricultural extension decreased the level of profit inefficiency while age, herd ownership and farmer group membership increased profit inefficiency level. The study also identified several challenges confronting the maize farmers. The most critical challenges reported by farmers included financial constraints, high cost of ploughing and difficulty in acquiring chemical fertilizer.

As a means to improve profit efficiency of producers, the authors recommend that access to agricultural extension services to farmers should be improved. This is because farmers learn from extension agents and acquire knowledge and relevant information that help them to optimize yield and achieve higher efficiency.

Furthermore, expanding access to education in rural areas is another important measure required to increase the profit efficiency of smallholder farmers. Education improves the human capital which improves knowledge of yield-enhancing technologies. Education also improves smallholders' access to information leading to improved farm performance.

Farmers' most pressing constraint was financial, hence increasing access to credit is essential to enhance farm performance. Credit is necessary to purchase farm inputs and ensures timely farm operations. This is critical because smallholder farming is usually time-bound due to the dependence on rainfall for production. Failure to carry out major farm operations timeously could lead to severe crop failure. Also, farmers identified high cost of ploughing as the second most critical constraint. Hence, improving access to agricultural mechanization services is required to improve smallholder farming. Tractorization improves soil preparation and enhances soil aeration, while it also facilitates timely farm operations.

The respondents identified poor soils as one of the constraints to maize production. This was buttressed by the efficiency analysis which indicated that farmers with poorer soils experienced lower profit efficiency. Thus, training of farmers in soil fertility management is needed to enhance profit efficiency of farmers. This could be achieved by incorporating soil fertility management as a critical part of extension service delivery to farmers.

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