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Article

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GENERAL & APPLIED ECONOMICS | RESEARCH ARTICLE

Agricultural technologies adoption and smallholder farmers' welfare: Evidence from Northern Ghana

Abdulai Adams^{1*} and Emmanuel Tetteh Jumpah²

Abstract: Improving the welfare of smallholder farmers through the introduction of improved technologies has gained increased attention in recent times. The focus now transcends the mere development and introduction of these farming technologies to improve productivity alone. Policymakers, particularly those in developing countries now pursue the implementation of interventions that promote the use of improved technologies to advance the welfare of smallholder farmers. However, the impact of such intervention to inform future policy decisions remains largely lacking and under theorized. The current study, therefore, analysed the impact of technology adoption on smallholder farmers' welfare. We obtained data from 461 technology adopters and non-adopters by using purposive and simple random sampling. Using the propensity score matching technique, we estimated the impact of technology adoption on smallholder farm households. The results show that regional location, educational level, age, and Farmer Base Organisation (FBO) membership are the main determinants of technology adoption among smallholder farmers.

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PUBLIC INTEREST STATEMENT

Improved agricultural technologies are mechanisms, practices, and ideas that enable farm households to increase their yields for food security and incomes. Researchers are constantly working to develop these technologies to help increase productivity, improve the welfare of farmers, and make agriculture more profitable. However, the adoption of these technologies has remained low and uneven due to various reasons. While some technologies are easily adopted by farmers, others are not. Some technologies come as a set but some farmers may choose to adopt some aspects, leaving the other aspects of the technology set. As such, there are heterogeneous effects on the number of technologies adopted by farmers with implications on welfare. Identifying the factors that influence farmers adoption decision and how that impact on their welfare is relevant in designing appropriate policies that enhance the uptake of these technologies. Strengthening farmer-centred institutions and enabling access to complementary services (finance and input support) would make technology adoption more effective.

Technology adoption had a positive but statistically insignificant impact on welfare. Consumption and clothing expenditure increased with adoption but not healthcare. To improve the impact of technology adoption on smallholder farmer welfare, emphasis should be placed on business supporting/advisory services; agricultural extension outreach, finance/input support among others.

Subjects: Agriculture & Environmental Sciences; Sustainable Development; Rural Development; Economics

Keywords: Technology; smallholder farmers; welfare; consumption; clothing and healthcare expenditure

1. Introduction

Development of improved technologies, transfer to, and adoption by smallholder farmers is critical to improving the productivity and income of farmers, and ultimately reducing poverty (Wossen et al., 2017). The adoption of improved technologies has a positive and significant effect on the welfare of households (Ayenew et al., 2020; Mendola, 2007). It contributes to improved food security (Justice & Tobias, 2016) and increases the incomes of adopters (Kopalo et al., 2021; Teka & Lee, 2020). Increased consumption expenditures, as well as growth in household assets, have also been linked to the adoption of various crop and livestock technologies (Justice & Tobias, 2016; Teka & Lee, 2020). Despite the importance of improved technologies in transforming the agricultural sector and improving the welfare of smallholder farmers, access to these technologies remains an issue resulting in inefficiencies in production. The distributional impacts arising from technology adoption are also heterogeneous with farm size and gender playing key roles (Kopalo et al., 2021). For instance, the observed positive income and productivity effects of technology adoption, however, do not significantly translate into dietary diversity (Justice & Tobias, 2016), suggesting that more needs to be done in ensuring nutrition justice in society.

Smallholder agriculture remains the major contributor to food production in Ghana and accounts for more than 80% of total food production in the country (Kansanga et al., 2019). Meeting the food and nutritional needs of the population as well as creating jobs for the teeming youth hinges on agriculture. Nonetheless, smallholder agriculture has been undermined by a plethora of challenges including limited access to improved technologies, finance to support the adoption of new technologies, poor marketing, limited storage capacity, and poor transport infrastructures (Jayne et al., 2010; Kuivanen et al., 2016). Consequently, most smallholder farmers tend to rely on traditional methods of producing crops and animals that are often cost-ineffective and less productive (Kansanga et al., 2019).

Attempts by various governments and policymakers in the Global South to increase productivity has placed little emphasis on how much productivity improvements would result in welfare gains for farmers. The belief was that increase in farm output (increase income) will be used to finance/ improve indicators for welfare (consumption expenditure on nutrition, healthcare, clothing and housing) (Dawson et al., 2016). In reality, however, many farmers are still trapped in poverty. There is a paradigm shift in recent policy interventions (of both the state and non-state actors) as efforts seem to be geared towards improving farmers' productivity, increasing their income, and improving welfare. To make modern agricultural technologies accessible to smallholder farmers, research collaborations to develop and transfer technologies is critical. The Africa RISING project epitomizes such interventions given its provision of technical support (agronomic training) and inputs to increase productivity, improve the income and welfare of smallholder rural farmers in Ghana. Under the intervention, inputs supplied to farmers help in facilitating their adoption of the technologies through the concept of technology parks. Despite these interventions, rural-urban migration and the

high prevalence of poverty constitute developmental bottlenecks in northern Ghana (World Bank, 2015). Thus, the key question explored is whether farmers' access to improved technology is directly linked to improvements in innovation adopters' productivity and welfare. Understanding how technology adoption impacts farmers' productivity and welfare is essential to the effective implementation and monitoring of these policy interventions. Previous studies on this subject matter have focussed on immediate project outcomes (productivity and income) with little empirical evidence on the impact of such interventions on farmers' welfare (Darko et al., 2018). The current study contributes to the adoption literature by analysing the welfare impacts of technology adoption using three welfare indicators: consumption expenditures on nutrition, clothing and healthcare.

2. Technology adoption, determinants and farmers' welfare

The decision of farmers to adopt improved technologies as well as the speed of adoption is influenced by a multiplicity of economic, social, cultural and sectoral factors. Manda et al. (2020) found that cooperative membership increases the likelihood of technology adoption by 11% and 24% for inorganic fertilizer and crop rotation respectively. Agricultural extension visits, ownership of livestock, number of years of residing in the village (locality), and off-farm work participation are the significant factors influencing the speed of adoption of improved maize varieties. Ngango and Hong (2021) found that access to credit, risk-loving behaviour, and membership of farmers association positively affect the speed of adoption of improved maize seed and fertilizers. Anang et al. (2020) found that agricultural extension had a statistically significant effect on both adoption (improved seed) and farm income of participants in northern Ghana. Their study also highlighted the role of land endowments in determining the income level of farmers in technology adoption. Farmers in the Northern Region had a higher farm income effect than those in the Upper East Region at 1% level of significance due to land endowment. Furthermore, access to improved seed and information are essential to increasing adoption (Awotide et al., 2016). Ayenew et al. (2020) revealed that adoption decision and intensity depends on access to credit, agricultural extension visits, soil fertility, farm size, off-farm work, input market distance, and farmer experience.

Simoes et al. (2020) compared three adoption rates (slow, medium, and fast) via two groups of farm size (small and large) and revealed that depending on farm size and rates, technological adoption effects differ in the short and long term. Technology adoption is profitable since unit costs of production are lower with high-income shares for adopters. Similarly, Verkaart et al. (2017) found that technology adoption significantly increases household income thus, reducing poverty. While the adoption of a new technology favoured all farm sizes, the impacts on income were greater with small farm size holders.

The impact of technology adoption on the welfare of beneficiaries and the factors influencing adoption is well documented in the literature (Ayenew et al., 2020; Justice & Tobias, 2016; Kekonnen, 2017). In analysing the potential impact of improved agricultural technologies on smallholder's crop productivity and welfare in Ethiopia, Kekonnen (2017) found a positive and significant effect of improved technology adoption on crop productivity and welfare of farmers. However, larger household size negatively affects the welfare of households and this tends to reduce the gains generated from technology adoption. Previously, Amare et al. (2012) examined the causal impact of technology adoption on household welfare and reported that maize-pigeon pea adoption has a positive and significant impact on the income and consumption expenditures of households. Thus, farmers who adopt improved maize have about 30–33% higher income per capita compared to non-adopters. Maize and pigeon pea adopters have 15–22% higher consumption expenditures compared to non-adopters. Justice and Tobias (2016) observed significant increases in households' gross farm income (GH¢852.00) and consumption expenditures for innovative farmers in northern Ghana, which they attributed directly to the adoption of improved varieties of cereals. However, the positive productivity and income effects do not significantly translate into nutritious diets.

Improvement in farmers' welfare is conditional on farmer participation in the output market (Awotide et al., 2016). This means that, beyond agricultural technology adoption, commercialisation and access to output markets also impact farmers' welfare.

Teka and Lee (2020) analysed the impact of participation in integrated farm package programmes on smallholder farmers' welfare in Ethiopia. The results revealed that household income, consumption expenditure and asset per capita of the households increased across the 3 years surveyed. Participated households had a positive significant impact on their consumption expenditures and calorie per adult equivalent but the income and asset per capita of the household although positive were not significant. Participants in the programme had a 37.8% increase in household expenditure per adult equivalent and a 45.3% change in calorie intake per adult equivalent. This shows the positive role of the programme in boosting welfare, improving food security, and reducing poverty. Family size, the total area cultivated, livestock holding, and level of package integration were some of the factors that determined welfare. Similarly, Ayenew et al. (2020) observed that the adoption of improved maize and wheat has a positive and significant effect in enhancing farm households' welfare. Ogundar and Bolarinwa (2019) also observed a positive and significant effect of technology adoption on household welfare measures (nutrition and income) and indicators of farm production using the meta-analysis technique. However, the magnitude of the impact was relatively small (weak relationship). Ali and Awade (2019) observed that formal education and participation in extension programmes increases farmers' welfare. Increasing land cultivation and adopting intercropping techniques has a positive and significant impact on women's welfare. This suggests the need to support female farmers for greater welfare impacts.

Technology adoption by farmers is constrained by several factors. Fertilizer adoption and/or usage among smallholder farmers is very low in sub-Saharan Africa, partly due to insufficient financial resources to enable them to purchase fertilizers (Kekonnen, 2017). A study in Zambia to understand fertilizer technology adoption and effectiveness on maize revealed that depending on soil requirements, average maize yield response range from not significant (0) to 7 maize kg per fertilizer kg (Burke et al., 2019). The estimated average value cost ratio for most farmers was between 1 and 2, suggesting that fertilizer use was fiscally rational. However, outcomes are uncertain and transfer costs exist, making rational farmers rethink whether to adopt fertilizer or not (Burke et al., 2019). But the adoption of the fertilizer technology as specified was likely to improve yields and income of farmers. Liquidity constraints and risk aversion impact the adoption of sunflower varieties (Tibamanye et al., 2021).

Technology adoption among farmers is heterogeneous and is influenced by various factors. Some farmers are more receptive and entrepreneurial than others. Studies that examined the role of social learning from extension agents and neighbours on technology adoption have reported positive outcomes (Krishnan & Patnam, 2013; Ngango & Hong, 2021), suggesting that social learning matter for the adoption of new technologies. Social learning is also far more persistent than learning from extension agents (Krishnan & Patnam, 2013). While the initial impact of extension agents on technology adoption was found to be high, the effect worse off, in contrast to learning from neighbours. This suggests that the extension model may transmit useful information but it is ineffective in encouraging modern technology adoption.

In sum, the review has shown mixed outcomes relating to technology adoption. While positive and significant welfare outcomes of technology adoption have been documented by most studies, statistically not significant and negative outcomes also exist. Various factors including location, geography, and method of data analysis appear to influence these outcomes. Farmers' decisions to adopt improved technologies and the speed of adoption are conditional on various factors: farmer specific characteristics, (age, farm size, gender, etc.), assets holding/ownership (animals), institutional factors (extension service, credit facilities),

among others. Generally, though the adoption of technologies appears to have positive welfare effects on farmers, other welfare indicators such as clothing and healthcare expenditure are less explored.

3. Data and method

The data used in this study come from a survey of 461 households collected in March 2020. The total number of respondents used in the analysis comprises 237 technology adopters from the Africa RISING Project and 224 non-adopters. Firstly, three (3) regions of northern Ghana were purposively selected (see Table 1) since they were the project implementing regions in Ghana. For each region, the project was implemented in two districts (Table 1). Each district has two (2) communities in which the project had been implemented and all were selected making a total of 12 communities for the study. All the technology adopters (237) involved in the project were interviewed for the study. A quasi-experimental design study like this requires a control group to compare with the treated to estimate the outcome of the intervention. Simple random sampling was used to select 224 non-project beneficiaries from the same communities that serve as the control group. Just as the number of technology adopters varies from each district, the number of controls also varies accordingly. The total number of respondents interviewed in each region and district are presented in Table 1.

Northern Ghana covers about 64% of Ghana's landmass. The area has a unimodal rainy season with a prolonged dry season and it is ideal for the production of cereals and tuber (yam) crops. Animal production which serves as a source of income especially during the dry season is a major source of livelihood for households and it is prevalent. The income obtained from animal sales is mainly used to meet household needs with part invested in farm operations. The population density in the area is less than that of southern Ghana and both males and females are involved in agriculture. However, farm operations are highly divisive by gender with females mostly involved in planting, harvesting, and off-farm income activities.

Map of northern Ghana and project sites

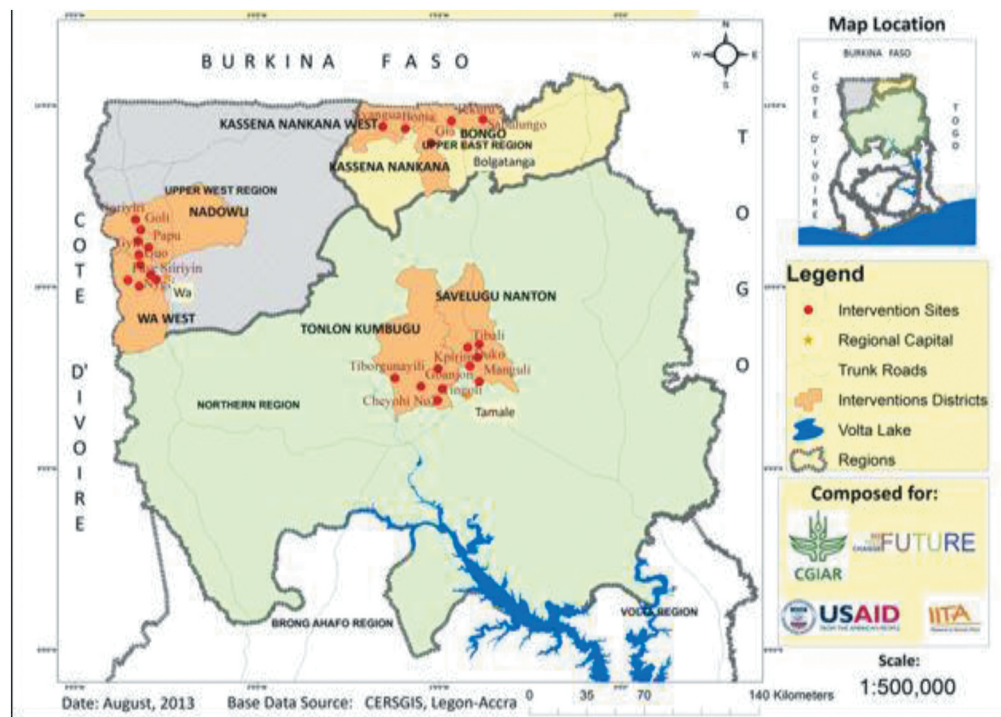
The variables used for estimation of the propensity scores and welfare and their measurements (Table 2) are derived from previous research¹ and knowledge of the study area. The treatment variable, technologies adoption, is in the form of 1 if the respondent is adopter and 0, otherwise. The study adopted some of the indicators used to measure welfare by the World Bank and OECD (expenditure on food consumption, clothing, and healthcare).² Consumption expenditure is the amount a respondent spends to provide at least two balanced meals (morning and evening) in a day and for a month for the household. Clothing expenditure is the amount of money spent on clothing for the entire household per month (which is normally done during festive occasions). Healthcare expenditure is the amount of money spent on health insurance that is used to finance

Table 1. Districts and number of respondents

Region	District	No of respondents	Percent
Northern Region	Tolon	63	13.7
	Savlugu	95	20.6
Upper West Region	Nadowli-Kaleo	91	19.7
	Wa West	70	15.2
Upper East Region	Bongo	79	17.1
	Kasina-Nankana	63	13.7
	Total	461	100

the cost of healthcare per month. Presented in Table 2 are the variables used in the study, their measurements and symbols.

3.1. Evaluation framework of matching



The impact of the treatment (Africa RISING Project) which is the difference between the outcome (s) of the treated (adopters) and the control group (non-adopters) represented by τ , is as expressed in [1]

$$\tau_i = X_i^1 - X_i^0 \tag{1}$$

X_i = the respondents, $X_i = 1$ if treated and $X_i = 0$, otherwise. To adopt or not, which is a decision of the farmer (that is observed) is model as [2]

$$ARP_i^* = \beta Z_i + U_i \tag{2}$$

$$ARP_i = 1, \text{ if } ARP_i^* > 0 \text{ } ARP_i = 0 \text{ if } ARP_i^* \leq 0$$

ARP_i = technologies adoption.

Z_i = factors influencing adoption of technologies.

U_i = error term

Table 2. Variables used to estimate the propensity scores, welfare and measurements

Variable	Symbol	Measurement	Expected Impact	Supportive literature
Outcome variables				
Consumption expenditure	CNE	Amount spent on food and nutrition in GH₵	+	Teka & Lee, 2020
Clothing Expenditure	CLE	Amount spent on clothing in GH₵	+	
Healthcare expenditure	HCE	Amount spent on healthcare in GH₵	±	
<i>Independent variables</i>				
Region of project	REG	Dummy (1 = Northern Region; Otherwise = 0)	±	
Location of farm	LOC	Dummy (1 = Upland; Otherwise = 0)	+	
Age	AGE	Years	±	
Educational level	EDU	Number of years in school	±	
Household size	HHS	Number of persons in a household	±	
Gender	GEN	Dummy (1 = Female; Otherwise = 0)	±	
FBO Membership	FBO	Dummy (1 = Member of FBO; Otherwise = 0)	+	Wossen et al., 2017
Credit received	CRR	Amount of loan received in the cropping season	+	Aynew et al., 2020
Extension service	EXT	Number of extension visit	+	Wossen et al., 2017; Anang et al., 2020
Farm size	FSZ	Hectare	+	Mendola, 2007

To analyse the relationship between adoption of technologies and expected welfare outcomes (consumption expenditure on nutrition, clothing and healthcare), a linear model is assumed and expressed as [3]

$$Y_i = \omega_i + \alpha_i X_i + \delta_i ARP_i + \varepsilon_i \tag{3}$$

Y_i = outcome(s) variables of i^{th} farmer,

ARP_i = adoption and non-adoption of technologies (dummy variable, 1 = adopter, otherwise = 0).

X_i = a vector of socio-economic characteristics of respondents

α_i = parameter of X_i

δ_i = parameter of APR

ω_i = constant term

ε_i = error term.

The model specification in [3] assumes the adoption of technologies as an exogenous variable on the basis that smallholder farmers will adopt technologies to improve their welfare (nutrition, clothing, and healthcare expenditures). But this may not necessarily hold as rich farmers can take advantage to participate and/or adopt technologies to obtain other benefits that may not be linked

to improvement in nutrition or healthcare. For instance, to get access to inputs for onward sales could make an influential community member adopt the technologies. The consequence is that adoption may not be random, with the selection of adopters being bias. Selection into a project based on “*whom you know*” is another example.

Using Ordinary Least Square (OLS) to estimate the outcomes in [3] will be biased especially if there is a correlation between the error terms in [2] and [3]. Using the instrumental variable method is an alternate approach to resolve the challenge. However, a linear functional form would be required, implying that both the treated and control group have variables that are akin. Essentially, the parameters may be different making the assumption unlikely to hold (Austin, 2011; Jalan & Ravallion, 2003).

Equation [3] requires a functional form and assumptions must be made for the model. But the Propensity Score Matching (PSM) procedure that is applied in this study does not require any such assumptions to estimate the association between the outcome variable(s) and the independent variables. In using the PSM, two conditions need to be met: Conditional Independence Assumption (CIA) and Common Support Condition (CSC) or Overlap conditions. The CIA states that the factors influencing the adoption of technologies should be observable to the researcher(s) and after controlling for these variables the potential outcome(s) should be independent of treatment(s) status. The CSC requires that individuals with the same or similar characteristics should have a positive chance of being an adopter or not (Heinrich et al., 2010). The implication is that opportunity for adoption or participation in a project should be random. However, after controlling for the factors influencing adoption it is still possible to notice systematic differences between adopters and non-adopters. These systematic differences may occur because some of the factors may not be observable (Smith & Todd, 2005). For example, the motivation of the farmer could not be captured. As suggested by Dehejia and Wahba (2002) a way to resolve the challenges associated with selectivity bias in an intervention is to use the matching procedure in evaluating the treatment effects. As noted by Heckman et al. (1999), the propensity score matching technique solves the problem of “limited distributional assumption of the errors” and enables the separation of the treatment on outcomes.

Two additional advantages that inform our choice of using the matching technique is its ability to identify biases (the original differences between adopters and non-adopters, and the difference between the treated and controls in the presence of treatment) and use the counterfactual approach (Austin, 2011; Winship & Morgan, 1999).

The Propensity Score (PS) is expressed in [4]

$$p(X_i) = pr[ARP_i = 1|X_i] = E[ARP_i = 1|X_i]; p(X_i) = F\{h(X_i)\} \quad (4)$$

Where $P(X)$ is the conditional probability of adoption given the pre-adoption characteristics (Rosenbaum & Rubin, 1983); ARP_i is the adoption of technologies; X_i is the vector of farmer socioeconomic and demographic characteristics; and $F[h(X_i)]$ is the normal or logistic cumulative distribution.

The logit or probit regression can be used to estimate the PS. Only mathematical reason influence the choice of using either the logit or the probit but the results from both estimation procedures are similar (see Caliendo & Kopeinig, 2008; Hujer et al., 2004; Owusu et al., 2011; Sianesi, 2004; Wossen et al., 2017). Like other studies, this study applied the logistic regression model. The outcome(s) or treatment effect(s) of the intervention were then estimated from the predicted propensity scores. The parameter of most interest in evaluation literature is the Average Treatment Effect on the Treated (ATT) which indicates the average impact of an intervention (ARP) on the treated (adopters). This is expressed in [5]

$$ATT = E[E\{Y_i^1 / ARP_i = 1, p(X_i)\} - E\{Y_i^0 / ARP_i = 0, p(X_i)\} | ARP_i = 0] \quad (5)$$

Nearest Neighbour (NN) matching (with or without replacement), Kernel and Local Linear Regression (LLR), caliper and radius matching, and stratification methods are some of the matching algorithms suggested in the literature for matching adopters and non-adopters of similar propensity scores. NN algorithm is the most widely used because of its ability to produce better estimates (reduced bias and variance) granted the overlap condition is satisfied. The NN is capable of matching all treated to control and in so doing remove the portion of bias, which allows for the use of existing dataset but still does not reduce the ability to match the last group (Caliendo & Kopeinig, 2008; Owusu et al., 2011; Rosenbaum & Rubin, 1985). To ensure that the estimates generated are not based on the choice of the algorithm, the current study used a combination of algorithms to ensure that the estimates are consistent and efficient.

Rosenbaum and Rubin (1985) also proposed the standardised bias approach (SBA) to check the quality of matches and sensitivity of the results. The SBA compares the results before matching and after that to assess if there still exists any difference even after conditioning based on the PS. If there is no difference after the matching then the estimates can be said to be stable. However, as argued by Hujer et al. (2004) it is still possible for unknown selection bias to arise if unknown variables happen to determine treatment variable(s) and outcome(s). Since in survey data it is impossible to estimate hidden bias magnitude, the *rbounds* were proposed by Rosenbaum (2002) to ameliorate the results. To check matching quality and the results or estimates Sianesi (2004) also proposed using the F-statistics and Pseudo-R². The method requires that after matching, the Pseudo-R² should fairly reduce and the F-statistics are statistically not significant. If this occurs, then the regressors are said to be well balanced and the estimates are efficient and consistent. The current study combined these approaches in certifying that the estimates are efficient and the results can be attributed to the intervention (technology adoption). The study used Leuven and Sianesi (2004) *psmatch2* for the estimations.

4. Results and discussions

The interpretation of scientific results especially in applied and social science should be guided by time, location, type of respondents and the methodology (Udry, 2018). We are guided by Udry's observation in analysing the findings.

4.1. Descriptive statistics

The means of the outcomes and independent variables, differences in means of the variables, and the pooled means are shown in Table 3. The statistics show that 51.4% of the respondents are adopters while 48.6% are non-adopters of the technologies. Among the outcome variables, it is only consumption expenditure that the difference in mean between the adopters and non-adopters is statistically significant at 1% (Table 3). On average, non-adopters spent more (GH¢ 18.00) on healthcare than adopters and two possible scenarios could account for this. First, non-adopters may not have adequate food and nutrition that may lead to frequent illness and hospitalisation, and hence increasing healthcare expenditure. Secondly, adopters may not have the financial resources to pay for their health insurance expenses. The former is likely to prevail since adopters spend more on consumption and clothing than non-adopters as revealed by the study.

The average years of formal education of both adopters and non-adopters are very low (about 2 years). This is so because about 80% of both the treated and control group did not have any form of formal education.³ This notwithstanding, the treated (adopters) spent fewer years (1.56 years) of formal education than the control or non-adopters (2.69 years) and the difference in mean between the two (1.13 years) is statistically significant at 1% (Table 3).

Adopters were older (49.64 years) than non-adopters (43.28 years) as revealed by the mean age and the difference in means is significant at 1% (Table 3). It appears that as farmers advance in age,

Table 3. Descriptive statistics of technology adoption

Variables	N = 237(51.4%)		N = 224(48.6%)		N = 13(2.8%)		N = 461(100%)	
	Adopters		Non-adopters		Difference		Combined	
	Means	SE	Means	SE	Means	SE	Mean	SE
<i>Treatment variable</i> (ARP-Technology adoption, 1 if adopter, 0 otherwise)								
<i>Outcome Variables</i>								
CNE	524.05	26.54	425.07	23.19	98.98***	35.40	475.95	17.83
CLE	266.81	17.42	252.25	15.24	14.56	23.25	259.74	11.62
HCE	150.32	8.46	168.04	16.88	-17.72	18.64	158.98	9.31
<i>Independent variables</i>								
REG	0.21	0.57	0.55	0.51	-0.34***	0.08	0.38	0.04
LOC	0.53	0.03	0.61	0.03	-0.08**	0.5	0.57	0.02
AGE	49.63	1.02	43.28	0.84	6.34 ***	1.32	46.54	0.64
EDU	1.56	0.30	2.69	0.22	-1.13***	0.36	2.11	0.18
HHS	8.27	0.33	7.95	0.28	0.33	0.43	8.12	0.21
GEN	0.86	0.02	0.88	0.22	0.02	0.03	0.87	0.02
FBO	0.94	0.03	0.29	0.12	0.62***	0.03	0.62	0.02
CRR	166.50	16.33	119.60	14.50	46.90***	21.78	143.66	10.93
EXT	3.23	0.08	2.78	0.09	0.47***	0.12	3.01	0.06
FSZ	2.11	0.12	1.92	0.17	0.19	0.04	20.2	0.08

Definition and measurement of variables remain the same as in Table 2.

*, **, ***, significant at 10%, 5% and 1% respectively. SE is standard error and N is the number of observations.

they participate more and/or adopt improved farm technologies as they gain more experience. Also, in the Ghanaian context, reverence is given to the elderly. Therefore, as farmers advance in age, they are likely given more opportunities to participate in projects and may adopt technologies thereafter. This trend is unlikely to continue without a turning point since individuals' strength to carry out farm operation will wane with increasing age. A statistically significant difference in means is observed for other variables in Table 3. It is only HHS, FSZ, and GEN that the mean differences are statistically not significant. This is no surprise because 99% of the respondents revealed there is an equal chance of participation in the project by both males and females. Concerning FSZ, these are smallholder farmers with similar farm sizes and therefore FSZ are likely to be homogeneous.

4.1.1. The logistic regression

The study adopted the logistic regression model to analyse the impact of the project intervention using the Propensity Score Matching (PSM) procedure to determine the propensity scores of the variables determining participation and/or adoption of the technologies. Table 4 provides the predicted propensity scores of the logistic regression with their statistical significance. The model results show a $p > \text{Chi}^2$ of 0.000 and Pseudo R^2 (0.43). This means that the model is asymptotically significant at 99% and the independent variables explain about 43% of the variations in the dependent variable. The variables that are statistically significant in determining adoption of the technologies are the regional location of the farmer, age, educational level, Farmer Based Organisation (FBO) membership, and the number of extension visit. While age, FBO membership, and the number of extensions visit influence adoption positively, regional location, and educational-level influence adoption negatively.⁴

4.2. Impact of technologies adoption on welfare outcomes

As Susser (1973) noted "consistency is present if the result is not dislodged in the face of diversity ... The strength of the argument [result] rests on the fact that diverse approaches produce similar results" (as cited in Rosenbaum, 2001). Following Susser, we analysed the data applying different algorithms to show if the statistical significance would be altered depending on the choice of algorithms. As indicated by

Table 4. Logistic regression results

ARP	Coefficient	S.E	z	P> z
REG	-0.774	0.184	-4.21	0.000***
LOC	-0.075	0.289	-0.26	-0.643
AGE	0.022	0.010	2.21	0.027**
EDU	-0.067	0.031	-1.91	0.046**
HHS	-0.005	0.311	-0.35	0.850
GEN	-0.144	0.407	0.19	0.724
FBO	3.828	347	-0.35	0.000***
CRR	-0.000	0.000	-0.15	0.878
EXT	0.225	0.106	2.12	0.034**
FSZ	-0.002	0.039	-0.05	0.962

N = 459; LR Chi²(10) = 271.52; p> Chi² = 0.000; LL = -182.208; Pseudo R² = 0.427

S.E (standard error), p> chi² (p-value), LL (Log likelihood), N (Observations).

*, **, ***, significant at 10%, 5% and 1%, respectively.

Heinrich et al. (2010), a result that is statistically significant and remains the same after combining various algorithms can be said to be consistent and efficient. Monthly expenditure on nutrition, clothing and healthcare were used as proxies for welfare and the results obtained are presented and discussed in line with that.

4.2.1. Consumption expenditure on nutrition

The impact of technology adoption on the welfare of adopters using consumption expenditure was analysed and the effects estimates (ATT) are reported in Table 5.

Table 5. Estimates of effects of technology adoption on welfare outcomes

Variable	Algorithms	Sample	Treated	Controls	Difference	S.E.	T-stat
	NN(5)	U	525.64	426.08	99.56	35.51	2.80
		ATT	531.11	484.33	46.77	87.41	0.54
CNE	Caliper(0.001)	U	525.64	426.07	99.55	35.51	2.80
		ATT	637.61	530.11	107.49	102.47	1.05
	LLR	U	525.64	426.08	99.56	35.51	2.80
		ATT	531.11	484.01	47.09	-	-
	Kernel	U	266.12	253.16	12.97	23.33	0.56
		ATT	273.55	252.45	21.10	44.22	0.48
CLE	NN(5)	U	266.12	253.16	12.10	23.33	0.56
		ATT	273.55	255.78	17.77	47.31	0.38
	LLR	U	266.12	253.156	12.10	23.33	0.56
		ATT	273.55	250.71	22.84	-	-
	NN (1)	U	150.32	168.58	-18.26	18.676	-0.98
		ATT	152.14	165.87	-13.72	36.56	-0.38
HCE	NN(5)	U	150.32	168.58	-27.43	27.52	-0.98
		ATT	152.14	179.57	-27.43	27.52	-1.00
	Kernel	U	150.32	168.58	-18.26	18.68	-0.98
		ATT	152.14	177.57	22.84	45.16	-0.56

U (Unmatched), ATT (Average treatment effect on the treated).

This study did not observe a statistically significant effect of technology adoption on consumption expenditure on nutrition (CNE) of the treated group since the T-statistics is less than 1.65 (Table 6). However, it found that CNE increased by almost GH¢ 47.00 (46.77) more for the treated group than the control (non-adopters) for the nearest neighbour with replacement 5 (NN (5)). The implication is that the treated group is more likely to have increased income or better farm output as a result of the technologies adoption for which reason adopters can spend more on food or have more nutritious food to consume than the control group (non-adopters). Although the result is not statistically significant it confirms that the intervention/technology adoption is a good choice for improving the CNE of smallholder farmers in rural communities. This outcome supports recent findings by Teka and Lee (2020), Ayenew et al. (2020), and Kopalo et al. (2021) that the adoption of various improved technologies impacts positively on farmers welfare (using consumption expenditure).

4.2.2. Clothing expenditure

Since the covariates and treatment variables for the intervention are the same for all the expected intervention outcomes, the propensity score estimates (Table 1) will remain the same for the remaining outcomes. The analysis of the results did not show evidence of a statistically significant effect of technology adoption on clothing expenditure (CLE). Before this study, it was anticipated that the treated group would have a higher yield and income than the control group since they adopted the technologies. Income accrued from the farm was expected to be used to pay for clothing for the households, especially during festive occasions. Although the study did not observe a statistically significant impact of technology adoption on CLE, there is still a difference between the treated and control group by almost GH¢ 21.10 per month (Table 5) which translates to about GH¢ 252.00 per year. This means that, on an annual basis, the treated group are likely to have extra income to spend on clothing than the control group due to their participation and/or adoption of the technologies.

4.2.3. Healthcare expenditure

Good health is crucial for continuous and sustained agricultural production and technologies adoption. Improved productivity and incomes of beneficiaries adopting technologies are expected to impact positively the healthcare of adopters. The study results using the nearest neighbour (NN) with replacement (1) matching algorithm revealed that the treated group spent less (GH¢ 13.72) on healthcare than the control group (Table 5). A similar result emerged for the NN matching algorithm with replacement 5 where the treated group spent GH¢ 27.42 less than the control group on healthcare. Furthermore, the kernel algorithm reports a difference of -27.57 between the treated and the control group suggesting that the control group spent more on healthcare than the treated. In all three algorithms analysed, the outcome was statistically not significant. The T-statistics were less than 1.65 suggesting that the choice of a matching algorithm could not have altered the estimates (Table 5). The implication is that the results obtained are consistent and efficient.

The results presented show a positive but statistically not significant impact of technologies adoption on the welfare of smallholder farmers. Studies like Ogundar and Bolarinwa (2019), and Justice and Tobias (2016) also found results that were similar to our findings when they analysed the impact of agricultural innovations on farm households' welfare. In addition, Amare et al. (2012) and Kekonnen (2017) also found a positive impact of technology adoption on the income and welfare of smallholder farmers. Conversely, Kekonnen (2017) found that the positive impact on household welfare is negated by large households' size. Unlike our study, their study found a statistically significant impact. These differences could be the results of the nature of the interventions, places, time, respondents, and method design.

The major challenge to technology adoption to improve the welfare of smallholder farmers as found by the study is the lack of finance to completely adopt the technologies. About 59.8% of adopters revealed this as the most pressing challenge inhibiting the complete adoption of the technologies. For instance, planting in a row improves productivity; however, it is labour demanding, which many rural farmers cannot afford to hire. To obtain optimum productivity, a farmer is expected to use a specified amount of

inputs (e.g., fertilizers, seeds) per hectare, which many farmers cannot afford. These challenges could have influenced the outcome of the intervention.

4.3. Matching quality test and robustness of estimates

4.3.1. CNE

The Propensity Score Test (pstest) results reported in Table 6 shows that all the variables used in the model were statistically not significant after matching, suggesting that the matching technique applied has helped to balance the covariates. For instance, FBO membership as a variable determining technologies adoption had a *p*-value of 0.000 before matching but after matching it had a value of 1.000 (Table 6).

Table 6. Matching quality test			
	Variable	Unmatched (U), Matched (M)	p> t
HNE	FBO	U	0.00
		M	1.00
	REG	U	0.00
		M	0.17
CLE	AGE	U	0.00
		M	0.97
	CRR	U	0.00
		M	0.35
HCE	AGE	U	0.00
		M	0.42
	EDU	U	0.00
		M	0.48

The result (Table 5) shows that regardless of the choice of algorithm, technology adopters always have higher expenditure on consumption or more food available than the control group. Also, the T-statistics in all the algorithms is less than 1.65, meaning statistically not significant outcome. For example, the caliper (0.001) shows a difference of GH¢ 107.49 on expenditure on consumption between the treated and control group, while the T-statistic is 1.05.

Table 7. Standardised bias and sensitivity analysis							
Variable	Sample	Pseudo-R ²	LR Chi ²	p> Chi ²	Mean bias reduction	Median bias reduction	Variance reduction
CNE	U	0.418	265.78	0.000	38.8	24.4	57
	M	0.041	9.09	0.524	11.1	7.4	14
CLE	U	0.418	265.78	0.000	38.8	24.4	57
	M	0.014	9.09	0.566	7.0	8.4	43
HCE	U	0.411	256.85	0.000	38.2	24.4	71
	M	0.020	11.61	0.312	10.1	8.4	29

U (Unmatched); M (Matched).

Furthermore, to ensure that the results obtained are based on observable covariates in the dataset, a bias trade-off analysis was conducted so that the result of the study is attributable to the intervention (technology adoption). The bias trade-off analysis requires that after matching the Pseudo R^2 should be fairly low and the p -value ($p > \text{Chi}^2$) should be statistically not significant. Rosenbaum (2001) proposed a 20% reduction. However, the results of Table 7 shows a 90.2% reduction in the Pseudo R^2 . Also, the mean and median bias have fairly reduced as observed in Table 7.

4.3.2. CLE

The results of the matching quality (Table 6) show that the age of respondents and the amount of credit received were statistically significant at 0.000 and 0.000 respectively. However, after the matching, the same became statistically not significant with 0.969 and 0.349 p -values, respectively (Table 6). A similar situation is observed for all the remaining covariates and the matching quality is good (well-balanced covariates). The nearest neighbour with replacement (5), kernel and Local Linear Regression (LLR) matching algorithms were combined to analyse the impact of the intervention on clothing expenditure to examine if the outcome is consistent and robust. The results (Table 5) show that in all algorithms chosen the outcome is stable because the T-statistics are all statistically not significant and all the treated have higher CLE than the control group. The nearest neighbour with replacement (5) algorithms shows there is GH¢ 18.00 (17.77) per month difference between the treated and the control on clothing expenditure. The kernel matching algorithm reports a GH¢ 21.09 expenditure difference between the treated and control group while the LLR shows a GH¢ 22.84 difference between the treated and the control (Table 5). The consistency in the result shows that the estimate of the outcome is stable and is not influenced by the choice of the matching algorithm. The p stest results (Table 6) show that age and the amount of credit received before matching were statistically significant (p -values of 0.000 and 0.000 respectively) but the

Figure 1. Distribution of the propensity-matched and unmatched samples of CNE.

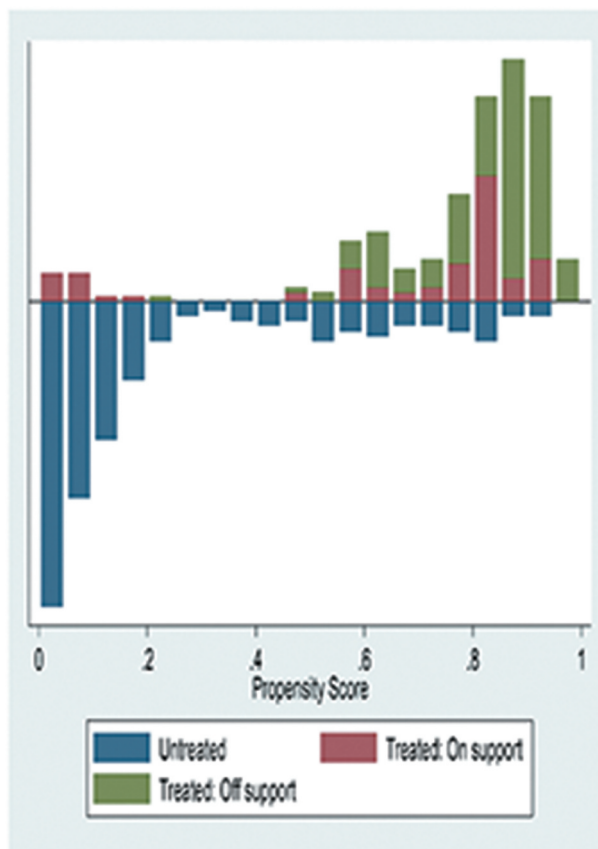
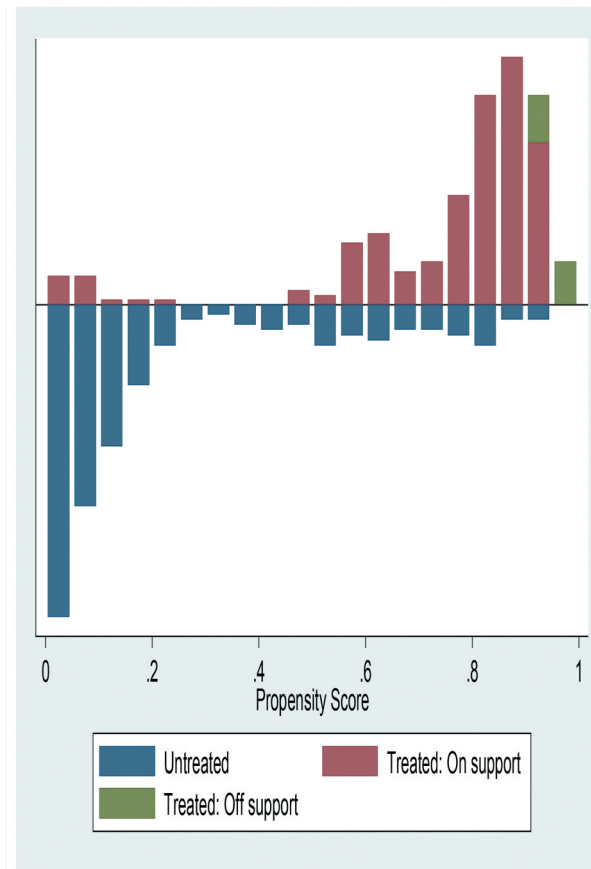


Figure 2. Distribution of the propensity-matched and unmatched samples CLE.



same show no statistically significant difference among the covariates (p -values of 0.42 and 0.48 respectively) after the matching. The sensitivity test (Table 7) also shows a reduction in Pseudo R^2 (0.42–0.01), mean bias (38.8–7.0) and likewise, the $p > \chi^2$ (0.57) is statistically not significant after matching.

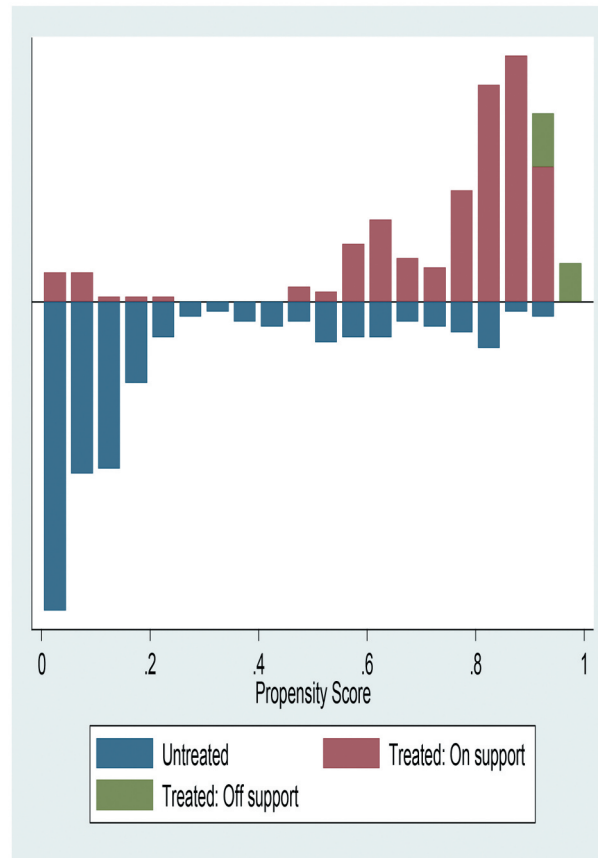
4.3.3. HCE

The result shows that after the matching there was no statistical significance among the covariates. For example, the location of the farmland recorded a p -value of 0.000 before matching, suggesting that there is a difference among the covariates. However, after matching, no such difference exists as it reported a p -value of 0.379 (Table 6). Again, the matching quality can be said to be good (well-balance the covariates for HCE). A combination of the algorithms also reported consistent and stable outcomes (Table 5) with T-statistics less than 1.65. The results (Table 7) show that the Pseudo R^2 , Log Ratio (LR), mean bias, media bias, and the variance have all fairly reduced after matching, suggesting that the result is robust and largely insensitive to hidden bias. The $p > \chi^2$ (0.312) is also not significant.

4.4. Common support and propensity scores frequency distribution

The common support condition requires that individuals (treated and controls) with the same covariates should have a positive probability of being adopters or otherwise. The common support condition whether met or not is determined by observing the distributions of the propensity score both treated and the control group. A substantial overlap of the distribution suggests common support, otherwise, a re-specification of the model may be required (Caliendo & Kopeinig, 2008; Heinrich et al., 2010). We followed the approach of Caliendo and Kopeinig (2008) and Heinrich et al. (2010) by observing if there is a considerable overlap

Figure 3. Distribution of the propensity-matched and unmatched samples HCE.



of the propensity scores of both treated and controls. Figures 1–3 show a considerable overlap of the propensity scores in all the outcome variables which suggests that the CSC or overlap condition has been met.

Except for the caliper (0.001), in Table 5 only 8% (19) of the treated group were off support and 92% (217) were on support in all choices of algorithms for both clothing and healthcare expenditure. Propensity score frequency distributions for consumption expenditure (Figure 1) is reported for caliper 0.001 in Table 5. There were 190 treated that were off support for consumption expenditure on nutrition. However, there is an observed similarity or overlap in the density of the propensity scores of the treated and control as could be observed in Figure 1. This satisfies the common support or overlap condition. This also supports that matching quality and sensitivity tests conducted early on to ensure that the estimates are robust. The overlap reported in this study is much better than those reported by other studies (see Owusu et al., 2011).

5. Conclusions and recommendations

Using household-level data of 461 respondents from rural northern Ghana, we examined the potential impact of technologies adoption on the welfare of smallholder maize and cowpea farmers. Before that, we analysed the factors determining technologies adoption; necessary to estimate the impact. We provided both empirical and methodological procedures in the analysis. We found that the regional location of the farmer, age, educational level, number of extension visit, and FBO membership are the statistically significant factors determining the adoption of technologies. We also found a positive but statistically not significant impact of technology adoption on consumption expenditure on nutrition and clothing but not

healthcare. Consumption and clothing expenditures increased by GH¢ 46.77 and GH¢ 17.77 respectively, while healthcare expenditure declined by GH¢ 27.43 (NN[5] values). We found a consistently positive impact of technology adoption on welfare indicators; consumption expenditure on nutrition, clothing, and healthcare. The policy implication is that extending such interventions to other smallholder farmers should be helpful. However, complete adoption of the technologies is seriously hindered by inadequate finance, timely affordable input supply, and extension visit, and these need to be resolved.

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Notes

1. Discussed under technology adoption, determinants, and welfare by recent studies (see Awotide et al., 2016; Wossen et al., 2017; Ayenew et al., 2020).
2. Expenditure on accommodation was dropped since most respondents were residing in thatched houses owned by them and could not provide information on the cost of rent or the amount they were willing to rent it out.
3. Even with those with formal education, the majority (40.2%) had maximum of 6 years of schooling (primary education) while many stopped schooling at one stage or another.
4. Detail discussions of these variables are not done here due to space limitation.

Disclosure statement

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