Does Adoption of Improved Agricultural Technologies Impact Poverty and Food Security in the Sahelian Region of West Africa?

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Abstract

Poverty and food insecurity are the most critical challenges confronting many developing countries, particularly in Sub-Saharan Africa where agriculture is the primary source of livelihood for most of the population. Increased climate variability during the last four decades has made the agricultural environment in many developing countries more uncertain, resulting in increased exposure to both production and price risks, thus necessitating renewed efforts aimed at greater dissemination of improved agricultural technologies. In this study, we used data from a sample of 2240 households in Mali to examine the factors influencing the adoption of improved agricultural technologies and how adopting these technologies impacts households' welfare in terms of poverty and food security. We employed Endogenous Switching Regression and Propensity Score Matching methods to account for endogeneity and selectivity bias due to observable and unobservable factors. The results showed that adopting improved agricultural technologies significantly reduces poverty and food insecurity. Specifically, technology adoption reduced poverty headcount by about 10 percentage points. The results point to the need for disseminating improved agricultural technologies at scale to generate large-scale adoption for greater impact.
JEL classifications: C34; O12; O33; Q12; Q16; Q18

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1.0.Introduction

Africa is the fastest-growing continent globally and over half of the increase in the growth rate of the world population between now and 2050 is expected to occur in Africa and most importantly, the population in SSA would more than double between the years 2015 and 2050 (AGRA, 2015). With the high population growth rate also comes the considerable demand for food. To feed the rapidly increasing African population, the continent has resulted in colossal food importation which is not a sustainable means of attaining food self-sufficiency in the long run. Furthermore, about 11 % of the estimated 7.42 billion world population classified as extremely poor are concentrated mainly in the rural areas of Southern Asia and sub-Saharan African countries, and about 88 % of them have only agriculture as the primary source of their livelihoods (World Bank, 2018; UN, 2018). However, the increasing adverse effects of climate change are becoming a severe fundamental threat to agricultural productivity, food security, and the people's overall welfare in Sub-Saharan Africa (SSA), more especially on poor households who exclusively depend on agriculture (Kim et al., 2018).

The Sahel region of West Africa which stretches from Mauritania down to Eritrea and includes Mali, Niger, Burkina Faso, Gambia, Senegal, and Chad is especially vulnerable to changes in climate. This region which is mostly desert is characterized mainly by dryness and drought exacerbated by insufficient rainfall, leading to land degradation, soil fertility loss, and inadequate agricultural production. Recent studies show that temperatures in SSA might increase with more frequent droughts, erratic rainfall, intra-seasonal dry spells and incidences of flooding (Bernstein et al., 2008; Cairns et al., 2012; Mariotti, Coppola, Sylla, Giorgi, &Piani, 2011; Hadebe et al., 2016; Cairns et al., 2013; Christensen et al., 2007; Sivakumar et al., 2005). These climatic changes further threaten to adversely affect the already climate-sensitive agriculture production in the Sahel region. Moreover, agriculture in this region is dependent on rainfall, with low input use, and limited adoption of improved climate-smart technologies.

Agricultural productivity growth has the potential of increasing income and reducing poverty for most of the rural populace (Bachewe et al.,2017; Christiaensen and Demery,2007; Christiaensen et al.,2011). In drought-prone areas like the Sahel, the adoption of climate-smart agricultural technologies has the potential to increase agricultural productivity sustainably, mitigate environmental degradation, increase farmers' resilience, and stimulate inclusive growth (FAO,2010; UN,2011). Hence, international development agencies have worked in many rural areas of the Sahelian region, disseminating and increasing accessibility to various types of improved agricultural technologies and creating awareness of these technologies to encourage adoption and diffusion to increase agricultural productivity in the face of climate change. These improved agricultural technologies are the results of many years of intensive research trying to find adaptable technologies to this region.

Kumar et al. (2020) and World Bank (2007) reported that a growing number of improved agricultural technologies had been developed and promoted in recent decades to address a diverse set of goals that directly benefit farmers. These technologies include genetic improvements (Evenson and Gollin, 2003b), irrigation management techniques (Pereira et al.,2002), improved/integrated pest management strategies (Pingali and Rosengrant, 1994; Susmita et al., 2007), and climate-resilient (climate-smart) technologies (Khatri-Chhetri et al., 2019). Another newly developed technology with a potentially positive environmental externality is CO2 emission reduction (Maraseni and Cockfield, 2011; Maraseni et al., 2018). A vast body of literature has researched the factors influencing or driving the adoption of agricultural technology (see, Beshir and Wagary, 2014; Doss,2006; Doss, Mwangi, and Verkuijl, 2003; Feder, Richard, and Zilberman,1985; Feder and Umali, 1993; Ogada, Mwabu, and Muchai, 2014; Uaiene, Arndt, and Masters, 2009; Zeng et al., 2018), however with varied results and limited studies for the Sahelian region of West Africa, especially Mali. Similarly, an array of past studies has also examined the impact of improved technology adoptions; however, many of these studies focus primarily on one type of technology the farmers adopt. For instance, several of these past studies examined the impact of improved seed variety of a particular crop such as maize, rice, etc., fertilizer, or other improved technology. However, the impact of a farmer adopting at least one of the abundantly available improved technologies is still missing in the literature. Therefore, our primary focus is to fill this literature gap by examining how the poverty, food security, and welfare of the farm household has increased or reduced if the household adopts at least one or any improved agricultural technology from the basket of improved agricultural technologies disseminated and made available for adoption. The "basket" of improved agricultural technologies contains improved seed varieties of different crops, fertilizer, and agrochemicals. Estimating the appropriate impact of adopting any improved agricultural technologies on poverty, food insecurity reduction, and improved rural households' welfare is crucial as it will guide the policymakers, development experts, Non-Governmental Organizations (NGOs), farmers, and extension agents on the appropriate strategies to adopt in relation to the Malian farm households' sustainability and survivability.

To achieve our objectives, we employed selectivity-corrected endogenous switching regression (ERS) models, and for robustness check, we also estimated a Propensity Score Matching (PSM) model using Nearest neighbour and kernel-based matchings. We define adopter as a farm household presently utilizing at least one of the numerous disseminated improved agricultural technologies such as improved varieties of different crops, fertilizer, agrochemicals (insecticide, herbicides, e.tc.). The rest of the paper is organized as follows. Section 2 outlines the overview of agricultural production and improved technologies adoption in Mali. The conceptual framework and estimation strategy is presented in section three. Section four presents and discusses the data used in this study. The results are present and discussed in section five. Section six presents the conclusions and implications for policy.

2.0. Methodology

2.1. Conceptual Framework

Globally, many research efforts and funding have gone into the development and dissemination of improved agricultural technologies. Adopting these technologies is seen as the critical element needed to generate the much-desired increase in agricultural productivity. The subsequent potential increase in the farm households' income because of the increase in marketable surplus would lead to an increase in food security and poverty reduction. However, promoting or disseminating improved agricultural technologies will not automatically boost agricultural productivity, increase livelihoods, and alleviate poverty (Tittonel,2007). The potential effect of agricultural technologies depends on the adoption by the farmers. Adopting these technologies is seen as the critical element needed to generate the much-desired increase in agricultural productivity, making the households to be self-sufficient in food production, generating more marketable surpluses that, when sold in a profitable output market, will increase income, and ultimately reduce poverty. The combination of the food security/food availability and poverty reduction will improve the overall welfare of the rural households.

The models of adoption are commonly grounded on the theory that agriculturalists make production choices with the main aim of maximizing their anticipated profits or utility. On the other hand, farmers' utility depends on optimizing productivity and diminishing farming costs to achieve maximum returns. The rural farm households are assumed to be heterogeneous and face constraints in adopting improved agricultural technologies. Among many others, the constraints are notably resources, information, and the accessibility of the technology (Foster and Rosenzweig, 2010). According to Feder et al. (1985), farm households adopt new technology when they expect a more profitable outcome than what they gained from the existing technology. Therefore, improved agricultural technology will only be appealing to households if the expected benefits significantly compensate for the costs. Hence, households' decision to adopt the improved technology may be viewed through the lens of constrained optimization where the household chooses the technology if it is available, affordable, and its usage is expected to be beneficial (de Janvry *et al*., 2010).

Influencing the expected benefit, the farm household derives from the adoption of the agricultural technology are a set of variables that are observable to the researcher M_i, those that are not observable β_i and independently and identically distributed (*i.i.d.*) error term τ_i. Denoting T_i as a binary indicator of improved agricultural technology adoption and $E(U^*)$ as the expected utility to be derived from the improved technology, a household's decision to adopt or not to adopt any improved agricultural technology depends on the net gains that might result from its adoption A rational farmer would adopt the improved agricultural technology if and only if she/he expects a higher utility from the adoption *i.e.* if $E(U^*) > 0$. Optimizing utility may also include considerations such as health benefits, environmental concerns, food security and risk (Ribaudo 1998; Napier et al. 2000).

The outcome variable G_i is also a function of observable variables including household characteristics (W_i), improved agricultural technologies adoption (T_i), unobservable variables such as intrinsic abilities, skills, and managerial competence (α_i), and iid error term (ϕ_i). The adoption of any of the improved agricultural technologies and outcome equations are represented as follows:

$$T_i = T_i(M_{i,}\beta_{i,}\tau_i) \quad (1)$$

$$G_i = G_i[W_i, T_i(M_i, \beta_i, \tau_i)\alpha_i, \phi_i] \quad (2)$$

The observed variable in the adoption (selection) and outcome equation (*W* and *M*), and the unobserved variables $\beta \ and \ \alpha$ can be correlated. Therefore, there is a need to investigate the interdependence between improved agricultural technologies adoption equation (1) and the outcomes equation (2).

2.2. Estimation Strategy

In evaluating the impact of a project or agricultural intervention, such as adopting improved agricultural technologies, the main challenge that most investigators face is to ascertain what would have happened to the recipients/adopters if the program/intervention had not occurred (Khandker et al.,2010). In the ideal world, we could identify the impact of adopting improved technologies by using a Randomized Control Trial (RCT) design. A randomly chosen group of farm households would be allowed to obtain and adopt the improved agricultural technologies. In RCTs, selection bias is zero since the treatment (intervention) is randomly assigned; hence the farm households assigned to the treatment and control groups differ only through their exposure to the treatment (Duflo et al.,2007). Thereby, the RCT design would allow us to compare the outcome from the treated group (adopters) with those of the control group (non-adopters) that did not receive the improved technologies. If the exposure to improved agricultural technologies is not random, the farm households either self-select into adoption or implementers target technologies dissemination at selected households (Alene and Manyong, 2007). Hence, the adoption of improved agricultural technologies is considered potentially endogenous.

Many factors can bring about selection bias. Self-selection bias-which occurs when farmers with favourable characteristics self-select into the adoption of improved agricultural technologies. Another selection bias source is the program placement bias, which usually happens when development experts disseminate improved agricultural technologies to selected relatively progressive farmers with experience in crop production. Thus, the farmers selected into the treatment group are likely to have characteristics that could allow them to be more successful in using the technologies than the average farmer. For example, if the adopters are only the most skilled, well-trained, or inspired and motivated farmers, then the inability to effectively control for these variables mentioned above would lead to an upward bias. Therefore, it would be erroneous to directly compare adopters of improved agricultural technologies to a randomly selected group of non-adopters.

In the absence of RCT, we utilized cross-sectional data. Selection bias and endogeneity are usually the main problems when using cross-sectional data. Failure to account for selectivity bias and endogeneity would hinder the real impact of the technology. Recent developments in the econometrics literature estimate causal effects using non-experimental techniques possible even in the absence of RCT. Our primary interest in this study is to estimate the average effect of adopting improved agricultural technologies on welfare, poverty, and food security for the adopting households, which is the Average Treatment Effect on the Treated (ATET). We address the selection and endogeneity problems by utilizing the endogenous switching regression (ESR) model (Lokshin and Sajaia, 2011; Malikov and Kumbhakar, 2014) and Propensity Score Matching (PSM) as a robustness check. The ESR model account for endogeneity by estimating a simultaneous equations model with endogenous switching by full information maximum likelihood (Lokshin and Sajaia, 2004). The ESR is a model widely adopted in the literature (e.g., Abdulai and Huffman, 2014; Khonje et al.,2015; Asfaw, 2010).

Although the ERS model relies on normality assumptions like the Instrumental Variable (IV) methods, the approach is more efficient than instrumental variables. Through modeling both selection and outcome equations, ESR has the advantage of controlling for factors that affect the treatment itself and disentangling the factors influencing the adopter and non-adopter groups (Besley and Case, 2000). Besides accounting for selection bias arising from unobserved factors that potentially affect improved agricultural technologies adoption and the outcomes, the ESR model controls structural differences between improved agricultural technologies adopters and non-adopters regarding the outcome functions (Alene and Manyong, 2007; Seng, 2016). In general, the ESR model's advantage is that it deals with self-selection bias caused by heterogeneity in observed and unobserved household characteristics, resulting in robust estimates of the intervention's impact on individual adopters' outcomes (Maddala,1986). Previous empirical studies have employed the framework to study the impact of modern technologies on food security and welfare (Asfaw *et al*., 2012; Khonje *et al*., 2015; Shiferaw *et al*., 2014; Coromaldi *et al*., 2015) and the impact of climate change adaptation on food security (Di Falco *et al*., 2011) among many others.

2.2.1. Endogenous Switching Regression

Think About a farm household i that is confronted with a decision on whether to adopt or not to adopt any improved agricultural technology. If we take the indicator variable to be T_i taking the value of one for the farm households that decide to adopt at least one of the disseminated improved agricultural technologies such as improved seed variety, fertilizer, and agrochemicals, and zero otherwise. Thus, we have to two distinct possible conditions: a choice to adopt *(T=1)* and not to adopt *(T=0).* Thus, we have two groups of farm households namely adopters, and non-adopters. If we denote the benefits to the household of not using improved agricultural technology by U_0 and the benefit derived from the adoption by U_1. Under a random utility framework, a rational farm household would choose to adopt improved agricultural technology if the net benefit derived from adoption is positive i.e. $U_1 - U_0 > 0.$ The net benefit ($U^* = U_1 - U_0$ is represented by a latent variable which is a function of observable characteristics (M_i) and error term τ_i.

Conditional on the farm households' decision to adopt any improved agricultural technology denoted by a selection function T_i, there are two potential outcomes to the two group of farmers: The outcome without adoption (G_0)and the outcome with adoption (G_1). This can be presented as a potential outcome framework as follows:

$$G_i = (1 - T_i)G_{oi} + T_i G_{1i} \qquad (3)$$

$$G_i = \begin{cases} G_{1i} \ if \ T_i = 1 \\ G_{0i} \ if \ T_i = 0 \end{cases} \qquad (4)$$

The benefit from adoption (treatment effects or impact) is given as $G_1 - G_0$. However, the main issue is that either of the outcomes is observed for a random sample of the farm households causing a "missing data" problem (Heckman et al. 1997). Hence, calculating the simple difference and averaging cannot give the treatment effect or impact. In the endogenous switching model, we describe the farm household's behaviour with two outcome equations and a selection function that determines which regime the farm household falls into. We represent the farm households improved agricultural technology adoption decision by the following latent variable framework (Lokshin and Sajaia, 2004 and 2011).

$$T_i^* = \mu M_i + \tau_i \qquad (5)$$

With

$$T_i = \begin{cases} 1 \ if \ T_i^* > 1 \\ 0 \ if \ T_i^* \leq 0 \end{cases} \qquad (6)$$

Conditional on selection, the outcomes are represented by a switching regime as follows:

Regime 1 (adopters): $g_{i1} = \lambda_1 M_{1i} + \phi_{1i} \qquad if \ T_i = 1$ *(7)*

Regime 2 (Non-adopters): $g_{i0} = \lambda_0 M_{0i} + \phi_{0i} \qquad if \ T_i = 0$ *(8)*

M represent a vector of observable variables that drives the decision to adopt improved agricultural technologies, such as the socio-economic/demographic characteristics of the household head, etc. in the continuous equation the y_{ij} are the outcome variables (Income and per capita consumption expenditure (proxy for welfare); $\lambda_{1i} \ and \ \lambda_{0i}$ are vectors of explanatory variables assumed to be weakly exogenous; $\lambda_1, \lambda_0 \ and \ \phi$ are vectors of parameters to be estimated. The error terms of the continuous ($\phi_{1i} \ and \ \phi_{0i}$) and selection equation (τ_i) are assumed to follow a trivariate normal distribution with zero mean and non-singular covariance matrix presented as follows:

$$\psi = \begin{bmatrix} \sigma_\tau^2 & \sigma_{1\tau} & \sigma_{0\tau} \\ \sigma_{1\tau} & \sigma_1^2 & . \\ \sigma_{0\tau} & . & \sigma_0^2 \end{bmatrix} \qquad (9)$$

Where σ_τ^2 is the variance of the error term in the selection equation and σ_1^2 and σ_0^2 are the variance of the error term in the continuous equations. Because of the correlation of the error terms in the selection equation with those in the outcome equations, the error terms' expected values in the outcome equations conditional on the sample selection are non-zero (Di Falco et al. 2011). If the estimated covariances turn to be significant, improved agricultural technologies adoption and welfare, poverty, and food security are correlated, proving endogenous switching. Following past studies, the ESR model was estimated using the Full Information Maximum Likelihood (FIML) estimation (Clougherty and Duos,2015; Lee and Trost,1978; Lokshin and Sajaia, 2004).

Identification is critical in Instrumental Variable (IV) techniques. We used the exclusive restriction to identify both the ESR and ESP models better. The selection of exclusive restrictions hinges on economic and empirical studies. For the sake of identification, we used awareness as our instrumental variable. We noted that once the farmers are "exposed" to or aware of the technology, the farmers acquire all the necessary information about the agricultural technology attributes that could enable them to decide on whether to adopt the technology or not. As hinted by Ashby and Sperling (1995), with this complete information about the agricultural technology, the farmers can subjectively assess the technology from the point of view contrary to the scientists. Consequently, creating awareness about new agricultural technology is an essential precondition for adoption to occur. A rural farm household cannot by any means adopt a new, improved agricultural technology without being first exposed or being aware of the technology. However, being aware of technology cannot impact the farmers' outcomes. The impact of adopting agricultural technologies on any outcome of interest can only be possible if the farmer decides to adopt the technology.

After estimating the model's parameters, we estimated the conditional expectations or expected outcomes as follows: For the improved agricultural technology adopters who adopted:

$$E(g_{1i}|T_i = 1, m_{1i}) = m_{1i}\lambda_1 + \sigma_1\rho_1 f(\mu M_i)/F(\mu Z_i \qquad (10)$$

For improved agricultural technology adopters had they decided to use improved agricultural technologies (counterfactual):

$$E(g_{1i}|T_i = 0, m_{1i}) = m_{1i}\lambda_1 - \sigma_1\rho_1 f(\mu M_i)/(1 - F(\mu Z_i)) \qquad (11)$$

For improved technology adopters had they decided not to use improved technology (counterfactual):

$$E(g_{0i}|T_i = 1, m_{0i}) = m_{0i}\lambda_1 + \sigma_0\rho_0 f(\mu M_i)/F(\mu Z_i) \qquad (12)$$

For improved agricultural technology non-adopters who did not actually adopt:

$$E(g_{0i}|T_i = 0, m_{0i}) = m_{0i}\lambda_1 - \sigma_0\rho_0 f(\mu M_i)/(1 - F(\mu Z_i)) \qquad (13)$$

Following Heckman et al. (2001) and Di Falco et al. (2011), the ATET is computed as the difference between expected outcomes for farm households that adopted any of the improved agricultural technologies **(**eq.10**)** and the counterfactual (eq.12**).** The Average Treatment Effect on the untreated (ATUT) is computed as the difference between the outcome they would have obtained in the counterfactual scenario that they decided to adopt (eq. 13) and the expected outcome for the households who did not adopt any of the improved agricultural technologies (eq.11). the conditional expectation equations are also used to calculate the heterogeneous effects (Di Falco *et al*.,2011; Carter & Milon, 2005). The farm households that use improved agricultural technologies may have better welfare, poverty and food security than the households that did not use although they decided to use, but because of unobservable characteristics such as skills and knowledge *i.e.* the effect of base heterogeneity (Carter & Milon, 2005). The computation of the effect of base heterogeneity for the farm households that decided to adopt (KL_1) and for the household who did not adopt improved agricultural technologies (KL_0) is indicated in Table 1. Another important statistic is transitional heterogeneity (TL) which measures whether the effect of the improved agricultural technologies adoption is larger or smaller for households that adopted or for households that did not, in the counterfactual case that they did adopt (Di Falco *et al*., 2011).

Table 1: Conditional expectations, treatment, and heterogenous effect

Sub samples	**Decision Stage**		**Treatment effects**
	To adopt	**Not to adopt**	
Adopter households	(a) $E(g_{1i|}T_i = 1)$	(b)$E(g_{0i}|T_i = 1$	ATET
Non-adopter households	(c) $Eg_{1i}|T_i = 0)$	(d)$Eg_{0i}|T_i = 0)$	ATUT
Heterogenous effects	KL_1	KL_0	TL

Note:

(a) ATET: The effect of treatment (adoption) on the treated (adopter households)

(b) ATUT: The effect of the treatment on the untreated (non-adopter households)

(c) KL_i: The effect of base heterogeneity for households that adopt (T=1) and did not use (T=0)

(d) $TL = TT$−TU is the transitional heterogeneity

2.2.2. Endogeneous Switching Probit Model (ESPM)

Estimating the impact of improved agricultural technology adoption on binary outcomes such as poverty headcount and food insecurity is also our interest in this paper. In contrast, for continuous outcome variables, accounting for sample selection and endogenous switching for binary outcomes where the data is fit applying non-linear models is problematic (Heckman,1978, 1986; Miranda and Rabe-Hesketh, 2006). Consequently, evaluations using two-stage procedures (such as Heckman's sample selection model) would lead to misleading inferences and create inconsistent conclusions. Consequently, we utilized the Endogenous Switching Probit (ESPM) framework, comparable to the endogenous switching regression for the continuous outcomes (Lokshin and Glinskaya, 2009; Lokshin and Sajaia, 2011; Miranda and Rabe-Hesketh, 2006). The demonstration of the impact of adopting improved agricultural technologies on the farm households' poverty and food insecurity status using the ESPM model was accomplished in two distinct analytical stages. The first stage is the decision to adopt any of the numerous yield-enhancing improved agricultural technology, and it was estimated using a probit model. In the second stage, we applied a probit regression with selectivity correction to explore the link between the binary outcome variables (poverty headcount and food insecurity) and a set of explanatory variables conditional on the farm households' decision to adopt. Let the following latent response models represent the farm households' decision to adopt any of the accessible or disseminated improved agricultural technologies:

$$T_i^* = M_i\gamma + \tau_i \qquad (14)$$

$$T_i = \begin{cases} 1, & if \;\; T_i^* > 0 \\ 0, & otherwise \end{cases} \qquad (15)$$

Where T_i^* represent a continuous latent variable, γ is a parameter to be estimated and τ_i is an error term. The binary response g_i is also defined as follows:

$$g_i^* = w_i\lambda + \mu T_i + \tau_i \qquad (16)$$

$$g_i = \begin{cases} 1, & if \;\; g_i^* > 0 \\ 0, & otherwise \end{cases} \qquad (17)$$

Where g_i are the most important outcome variables and g_i^* represents a continuous latent variable, λ represent a vector of parameters to be estimated, μ is the coefficient of the endogenous treatment dummy, and τ_i is a residual term. The endogenous switching problem, in this case is that the response g_i for the i^{th} household is not always observed. Besides, g_i is assumed to depend on the endogenous dummy T_i and a vector of explanatory variables, m_i. The endogenous dummy T_i also depends on a vector of explanatory variables m_i there is the possibility that vectors w_i and M_i are correlated. Direct estimation of equation 16 and interpreting as the causal effect would result in biased estimates due to unobserved endogeneity. The ESPM regression would correct this bias by simultaneously estimating the selection and outcome equation with proper instrumentation of the improved agricultural technologies adoption decision (Aakvik et al., 2000; Lokshin and Sajaia, 2011). The ESPM framework models the decision to adopt improved agricultural technology and its effect on various binary outcomes in a two-stage treatment framework. In the first stage, farm households' decision to adopt any improved agricultural technologies is modeled and estimated using a probit model. The use of a probit model with selectivity correction to determine the relationship between the binary outcomes, improved agricultural technologies adoption, and explanatory variables takes place in the second stage.

Following Lokshin and Sajaia (2011), we specified the binary outcomes conditional on improved agricultural technologies adoption as an endogenous switching regime model:

Regime 1(adopters): $g_{1i}^{*} = \lambda_1 W_{1i} + \phi_{1i}$ $\quad g_{1i} = 1(g_{1i}^{*} > 0)$ *(18)*

Regime 2 (Non-adopters): $g_{0i}^{*} = \lambda_0 W_{0i} + \phi_{0i}$ $\quad g_{0i} = 1(g_{0i}^{*} > 0)$ *(19)*

Observed g_i is a dichotomous realization of the latent variables and it is defined as:

$$g_i = \begin{cases} g_{1i,} & if\ T_i = 1 \\ g_{0i,} & if\ T_i = 0 \end{cases} \tag{20}$$

Where $g_{1i,}$ and $g_{0i,}$ are the latent variables that determine the observed binary outcomes g_1 and g_0 for improved agricultural technologies adopters and non-adopters, respectively. W_1 and W_0 are vectors of weakly exogenous variables; M_i is a vector of variables which determines a switch between the regimes; λ_1 and λ_0 are vectors of parameters to be estimated, and ϕ_{1i} and ϕ_{0i} are the error terms in the outcome equations. Following Lokshin and Glinskaya (2009) and Lokshin and Sajaia (2011), we estimated a Full Information Maximum Likelihood (FIML) endogenous switching probit model to estimate the parameters of interest. We also estimated the effects of improved agricultural technology adoption on the farmers' poverty and food insecurity status by adopting the methodological framework proposed by Aakvik et al. (2000) and Lokshin and Sajaia (2011). Additionally, the specified endogenous switching probit model allowed the derivation of probabilities in counterfactual cases (Ayuya et al., 2015). Using the formulas below, we estimated the Average Treatment Effect on the Treated (ATET) and the Average Treatment effect on the Untreated (ATUT):

$$TET_j = pr\left(g_{1j} = 1 \middle| T = 1\right) - pr(g_{0j} = 1|T = 1) \tag{21}$$

$$TUT_j = pr\left(g_{1j} = 1 \middle| T = 0\right) - pr(g_{0j} = 1|T = 0 \tag{22}$$

Previous studies that have used the ESPM among many others include (Ayuya et al.,2015; Gregory and Coleman-Jensen, 2013; Lokshin and Glinskaya, 2009).

2.2.3. Propensity Score Matching-PSM

It is possible for the results obtained from the ESR estimation to be sensitive to its model assumption, i.e., selection of instrumental variables. We deemed it imperative to adopt the PSM approach to verify the robustness of the estimated treatment effect results obtained from the ESR. According to DiPrete and Gangl (2004), PSM offers an estimate of the effect of a "treatment" (adoption) variable on an outcome variable that is essentially free of bias arising from an association between treatment status and observable variables. However, matching methods are not robust against "hidden bias" arising from unobserved variables that simultaneously affect assignment to treatment and the outcome variable.

The PSM controls for differences in observable covariates that might influence the decision of a rural farm household to adopt improved agricultural technology, and is based on the Conditional Independence Assumption (CIA)[9] which states that conditional on observables characteristic of the rural farm households (M) the outcomes are independent of the treatment written as: $TG_1, G_0 \perp T|M$ Another assumption is the common support or overlap condition: $0 < P(T = 1|M) < 1$. This condition ensures that the treatment observations have comparison observations "nearby" in the propensity score distribution (Heckman *et al.,* 1999). Expressly, it guarantees individuals with the same observable characteristics have an optimistic likelihood of being in both groups (Leuven and Sianesi,2003). We executed this prerequisite so that the estimation is performed on individuals with common support. Therefore, the average treatment effect on the treated (ATET) is the difference in the mean outcome of the matched adopters and non-adopters with common support conditional on the propensity score (Tommaso, 2007). Heckman *et al.* (1997) advise dropping treatment observations with weak common support. Intuitively, we can make inferences about causality only in the area of common support. It is also essential to conduct a balancing test. That is to check if:

$$\hat{P}(M|T = 1) = \hat{P}(M|T = 0) \qquad (23)$$

The propensity score (P(m)) which is the probability that a rural household will adopt any improved agricultural technology given M is written as:

$$P(m) = Pr(T = 1|M = m). \qquad (24)$$

Where: T= the adoption of improved agricultural technology

M= observable characteristics of the rural farm households

More importantly, estimating the propensity is not sufficient to calculate the Average Treatment Effect (ATE). It is vital to search for the appropriate counterfactual(s) that matches with each adopter, depending on its propensity score. Therefore, the next step is to choose a matching algorithm. The commonly used matching methods are the nearest neighbour and the kernel matching. The Nearest-neighbour matching matches adopters and non-adopters with the nearest propensity scores (Davis *et al.,* 2010). These matched non-adopter units served as a means to construct the counterfactual for the adopter units. The Kernel-based matching method measures treatment effects by subtracting from each outcome observation in the treatment group a weighted average of outcomes in the

[9] See Wooldridge, 2002

comparison group. Each non-adopter unit is weighted based on its distance from the adopter unit. Heckman et al. (1997, 1998) and Smith and Todd (2005) provided a general outline for understanding the different matching estimators. Using their framework, the three matching estimators of ATET can be represented in line with Hosny (2013) as follows:

$$ATET = \frac{1}{q^1}\sum 1\{(G_{1i}|T_i = 1) - \sum j c_{1,0}(G_{0i}|T_i = 0)\} \quad (25)$$

Where $q^1$the number of adopter cases and c represents a set of scaled weights that measure the distance between each non-adopter and the target adopters. These estimators differ primarily in the number of matches designated for each to-be-matched target case and how these multiple matches are weighted,$c_{1,o}$, if more than one is used (Morgan and Harding, 2006). The Treatment Effect on the Treated (ATET) is then estimated by averaging within-match differences in welfare, income, and poverty between the rural households that adopted the improved agricultural technologies and the non-adopters (see, e.g., Rosenbaum (1995), Dehejia and Wahba (1999) as follows:

$$E(G_1 - G_0|T = 1) = E[E(G_1 - G_0|T = 1, P(m))] \quad (26)$$

$$= E[E(G_1|T = 1, P(m)) - E(G_0|T = 0, P(m)]$$

Rosenbaum and Rubin (1983) showed that the farm households that adopted improved agricultural technology (treated) and the non-adopters (control) group with the same propensity scores have identical distributions for all baseline variables. Hence, this “balancing property” implies that if we effectively control for the propensity score when we compare the groups, we have succeeded in turning the observational data into a kind of randomized block experiment, where “blocks” are groups of subjects with the same propensities.

2.2.4. Poverty measurement

Income and consumption expenditure are the two most common indicators used in poverty assessment across the globe. However, in this study we used the per capita consumption expenditure to compute one of the most important variables in poverty analysis which is the poverty line. We constructed the relative Poverty line define as that level of per capita expenditure needed for a household to escape poverty. The poverty line was constructed using 2/3 of the mean per capita expenditure. Despite the availability of several poverty measurements developed and have been used in the literature (Sen, 1976; Foster, 1984; Foster and Shorrocks, 1988 and Froster-Greer-Thorbecke (FGT), 1984), the FGT (1984) often called the p-alpha class of poverty measure is the most popular and commonly used method for poverty assessment in the literature. The popularity of the FGT poverty measurement is posited to be because the α variable in the FGT equation is a policy parameter that can be varied to approximately reflect poverty “aversion”. Besides, the P_α class of poverty indices is subgroup decomposable.

Thus, this study adopted the standard FGT (1984) to generate the poverty profile of the selected farm households. Thus, we operationalized the standard FGT (1984) as follows:

$$P_{\alpha}(g,z) = \frac{1}{N}\sum_{i=1}^{n}\left(\frac{Z-g_i}{Z}\right)^{\alpha} \quad (27)$$

Where Z = the relative poverty line

n= number of farm households below the poverty line

N= number of farm households in the reference population

G_i = per capita consumption expenditure, i^{th} farm household

$Z - G_i$ = the poverty gap of the i^{th} farm household

$\frac{Z-G_i}{Z}$= the poverty gap ratio

α = the poverty aversion parameter and takes value 0, 1, 2

α = 0, equation (27) gives the poverty headcount

α =1, equation (27) gives the poverty depth

α =2, equation (27) gives the poverty severity index .

The poverty headcount: The headcount index is the mostly adopted method of estimating poverty incidence. This index estimates the proportion of the population that is considered poor.

The poverty depth: The poverty gap index measures the depth of poverty. That is how far, on average, households/individuals fall below the poverty line. This index shows how much cash should be transferred to the poor to lift them out of poverty. More precisely, this indicator presents the minimum cost for eliminating poverty with monetary transfers.

Poverty severity: The squared poverty gap index measures the severity of poverty: the degree of inequality amongst the poor households.

3.0. Variables

3.1. Outcome variables

The adoption of improved agricultural technology can increase productivity with the possibility of substantial marketable surpluses that would also increase household income. According to Headey (2013), higher incomes raise expenditure levels on food, increasing the quality and quantity of diets. Furthermore, income raises expenditure on nutrition-relevant and non-food expenditures, such as health, sanitation, electricity, water, and housing quality, thereby improving households' welfare. Thus, the outcomes of interest in this study are welfare, per capita household income, poverty, and food insecurity status.

Consumption expenditure and household income are the main variables for measuring welfare. This study took consumption as an indicator of welfare as it works relatively well in the context of developing countries (Ravillion,1992 and Cheema,2005). The welfare of the household is proxied by the per capita consumption expenditure. The household per capita consumption expenditure, per capita income, and per capita food expenditure were obtained by dividing the total household expenditure, total income, and total expenditure on food by the household size. The total household expenditure includes expenditure on food and non-food items. The total household income includes income from all crop production, livestock production, off-farm activities, non-farm activities, and remittances.

The farm household's poverty status is measured by the poverty headcount (proportion of households below the poverty line) and the per capita total household income. We calculated the food insecurity line and poverty line using 2/3 of the mean per capita food expenditure and per capita total household expenditure (food and non-food), respectively. The food insecurity line and the poverty line are used as a threshold based on which the households are classified into food-secure/ food insecure and poor/non-poor. A household with an average per capita food expenditure lower than the food insecurity line is classified as food insecure and food secure otherwise. Similarly, any household with a per capita consumption expenditure lower than the poverty line is classified as poor and non-poor otherwise. Therefore, we defined the poverty headcount as a binary outcome, taking the value of 1 if the household is poor and 0 otherwise, and food insecurity also takes the value of 1 if the household is food insecure and 0 otherwise.

3.2. Explanatory variables

The socioeconomic/demographic characteristics and institutional factors hypothesized to affect the outcome variables (welfare, income, poverty, and food insecurity) are like those hypothesized to affect the adoption of improved agricultural technologies. These variables were selected based on economic theory and empirical studies on technologies adoption and impact assessment (Asfaw *et al.*, 2012; Bezu *et al*., 2014; Coromaldi *et al*., 2015; Manda *et al*., 2016; Di Falco *et al*., 2011; Khonje *et al*., 2015; Mutenje *et al*., 2016; Shiferaw *et al*.,2014; Cunguara and Darnhofer, 2011; Awotide et al. 2012). Consequently, the main factors that are reported to influence the adoption of agricultural technologies and the outcome variables are the age of the household head, household size, number of years of schooling, farm size, awareness status, access to credit, migration, the primary source of income, literacy rate, membership of any organization, ownership of bank account (proxy for savings). We also included the average distance of the farmers' village to the nearest market to reflect the transaction costs that the household incurs, such that the greater the distance, the higher the costs.

4.0. Data and Sampling Framework

The study area is the republic of Mali. Located in the Sahelian region, Mali is one of the poorest countries in West Africa. A multistage sampling technique was adopted to draw an appropriate sample for the survey. In the first stage, four regions (Koulikoro, Sikasso, Segou, and Kayes) were purposively chosen based on the intensity of cereal and legumes production, agroecology, accessibility, and security. In the second stage, eight communes were selected, purposively from each of the chosen project regions. The final stage is the random selection of the households through the collaborating NGOs and communal consultation forum. We selected farm Households from both the intervention and non-intervention villages.

In total, the sample size for each for the intervention and non-intervention villages was 1120, making a total sample of 2240 households in Mali. This sample size was distributed evenly among all the selected regions. Therefore, the sample size per region for the intervention and non-intervention villages was 280 households each. The sample consists of seven households per village. We have 40 villages per commune for the intervention and non-intervention, making 80 villages per commune for the survey. The data collection instrument was a well-structured questionnaire. The questionnaire design for this survey enabled us to obtain precise, dependable, and valid information.

5.0. Results and Discussions

5.1. Variable Definition and Descriptive Statistics

Presented in Table 1 is the definition and description of some selected variables used for the empirical analyses. The descriptive analyses show that a considerable percentage of the sampled households (97 %) have farming as their primary occupation. About 91 % of the sampled households are aware of improved agricultural technologies. About 93 % of the farm households reported that they had received awareness about these agricultural technologies through the formal sources of information that comprises radio, television, newspaper, contact with extension agents, and participation at different trainings organized by research institutes and NGOs. However, about 75 % have adopted at least one of the disseminated improved agricultural technologies. In terms of demographic characteristics, about 99 % are male-headed households, and the household head's average age is 56 years. The average household size is seven persons.

Rural farm households' opportunity to participate in development programs and access to land for agricultural production in most cases depends on the households' residence status in the selected project intervention villages. Almost all the sampled farmers (98 %) are 'natives', residing in their respective villages for an average of 55 years. Besides, a significant percentage of the farm households (89 %) owned land for farming, and the estimated total farm size available for farming is an average of 13.51 ha, out of which only 8.31 ha is currently under crop production. The result further reveals an average land pressure of about three persons per hectare, and this indicates that the farmers could be having some challenges related to land access and is a pointer to the need for the farm households to adopt improved agricultural technologies to move away from extensive to intensive agricultural production. Only about 39 % of the household head are literate, with an average of about six years of schooling. About 81 % of the households are a member of an organization.

Table 2: Variable definition and descriptive statistics

Variable	Description	Mean (Std. Dev.)
Main occupation of household head	1 if the main occupation of the household head is farming, 0 otherwise	0.97(0.18)
Adoption	1 if the farmer adopts any of the improved agricultural technologies, 0 otherwise	0.75(0.44)
Poor	1 if the farm household is poor, 0 otherwise	0.60 (0.49)
Per capita consumption expenditure	Per capita consumption expenditure (CFA)	107739.8 (105209.8)
Gender	1 if the farmer is male, 0 otherwise	0.99 (0.09)
Age	Age of the household head in years	56.39 (14.77)
Residence status	1 if the farmer is a native of the village, 0 otherwise	0.98 (0.15)
Household size	Number of family members	7.57 (5.74)
Education	Number of years of formal education	6.39(4.35)
Owned land	1 if the farmer owned land, 0 otherwise	0.89(0.30)
Total farm size	The total farm size available for crop production(Ha)	13.51(10.56)
Average cultivated farm size	The average farm size currently under crop production (Ha)	8.31 (5.84)
Access to extension	1 if the farmer has access to extension, 0 otherwise	0.73(0.44)
Access to credit	1 if the farmer has access to credit, 0 otherwise	0.33(0.47)
Own a bank account	1 if the farmer owns a bank account, 0 otherwise	0.1381 (0.345)
Main income source	1 if the main income source is agriculture, 0 otherwise	0.609(0.488)
Distance to nearest market	Distance of farmer to nearest market (Km)	16.33(24.92)
Distance to nearest village	Distance of farmer to nearest village(Minutes)	25.57(46.01)
Residence in the village	Number of years of residence in the village	55.21(21.28)
Farming experiences	Number of years of farming experience	37.88(17.42)
Literacy rate	1 if farmer can read or write in French	0.39(0.49)
Awareness of improved technologies	1 if the farmer is aware of any of the improved technologies, 0 otherwise	0.91 (0.29)
Formal sources of information	1 if the farmer receives information from formal sources, 0 otherwise	0.93(0.26)
Membership of organization	1 if the farmer is a member of any organization,0 otherwise	0.81(0.39)
Migrant household	1 if at least one person has migrated from the household, 0 otherwise	0.49(0.50)
Attended training	1 if the farmer has participated in any training, 0 otherwise	0.24(0.43)

4.2. Adoption of Improved Agricultural Technologies

One of the strategies to reduce poverty through increased agricultural productivity is to promote the adoption of high-yielding improved crop varieties (Nkonya et al., 2004). As reported in the literature, various type of improved agricultural technologies has been disseminated and made available for the poor rural farmers to adopt. Table 3 below presents the most common improved agricultural technologies adopted by the sampled farm households in Mali. We designed this study to capture the impact of the farm households adopting any of the highlighted improved agricultural technologies. An adopter is a farm household that is currently adopting at least one of the highlighted agricultural technologies, and as a non-adopter, if the household is not using any of the agricultural technologies.

The results presented in Table 3 show that the farmers use improved seed variety of different crops: mostly cereal, agrochemicals such as inorganic fertilizer, and other improved agricultural practices such as seed treatment with chemicals before planting. About 29 %, 19 %, and 23 % of the farm households adopt improved seed varieties of maize, millet, and sorghum, respectively. About 44 % of the farm households adopted inorganic fertilizer, and about 14 % of the farmers treat their seed with fungicide before planting to reduce pest and disease attack.

Table 3: Adoption of Improved Agricultural Technologies

Available Improved Technologies (%)	Mean	Standard Dev.
Adoption of Improved seed varieties		
Improved maize seed variety	0.29	0.46
Improved millet seed variety	0.19	0.39
Improved sorghum seed variety	0.23	0.42
Improved vegetable seed variety	0.05	0.22
Improved cowpea seed variety	0.13	0.34
Improved soybean seed variety	0.01	0.07
Improved groundnut seed variety	0.10	0.30
Adoption of Agrochemicals		
Fertilizer	0.44	0.49
Herbicide	0.29	0.46
Chemical pesticides	0.15	0.36
Biological Pesticide	0.02	0.13
Aflatoxin	0.01	0.08
Other Improved practices		
Fertilizer mixed with seed before planting	0.07	0.25
Fertilizer micro dosing	0.09	0.29
Seed treatment with chemicals before planting	0.14	0.35

Source: IITA- CSAT project Mali (2019)

4.3. Test of Mean Differences in Socioeconomic/Demographic Characteristics

This section presents the mean differences in some selected poverty, food insecurity, and welfare indicators, between the adopters and non-adopters of improved agricultural technologies. Here, we tried to assess if the difference in all the selected welfare, poverty, and food security indicators between the adopters and non-adopters is statistically significant. The results revealed in Table 4 show that the farmers who adopted improved agricultural technology are not entirely identical to those that did not adopt. Those farmers who adopted improved agricultural technologies have statistically significantly higher household income, farm size, productive assets, and per capita consumption expenditure than those farm households that did not adopt any improved agricultural technology.

The mere comparison of the mean of this poverty, food security and welfare indicators of adopters and non-adopters of any improved agricultural technology after the dissemination/exposure to the improved agricultural technologies may lead to deceptive outcomes because the two groups (adopters and non-adopters) may have had different pre-treatment characteristics. Hence the difference in the mean outcomes between the two groups can be attributed to both the impact of adopting the improved agricultural technologies or pre-existing differences (selection bias) (Duflo et al.,2007). Hence, these results presented in Table 4 are referred to as "naïve impact estimate" because it produces a biased estimate of the impact in the presence of selection bias. Against this background, the findings are not a reflection of the real impact of the adoption of improved agricultural technologies on the outcomes of interest, neither do they indicate that those farm households that have adopted improved agricultural technologies are better in all the outcomes or in other variables than those that did not. This result is only a pointer to the fact that there is selection bias in the sample.

Table 4: Test of Mean Differences in Welfare, Poverty, and Food Insecurity Indicators

Variable	Total N= 2,217	Adopters N= 1,654	Non-adopters N= 563	Mean Difference	t-test
Total household income (CFA)	442948.20	499366.60	277200.20	222166.40***	8.63
Per capita total household income (CFA)	95384.01	109714.80	53752.93	55961.83***	5.49
Total income from crop production (CFA)	245705.40	293034.80	106659.40	186375.40***	9.58
Total non-farm income (CFA)	130038.40	138134.00	106254.80	31879.18***	2.72
Total consumption expenditure (CFA)	702620.50	752215.40	556919.10	195296.30***	3.52

Per capita consumption expenditure (CFA)	1 07739.80	115163.70	86173.06	28990.68***	5.65
Total non-food expenditure (CFA)	654604.90	700256.00	520489.50	179766.60***	3.31
Total Farm size (ha)	15.34	16.14	12.97	3.18**	2.38
Average Farm size cultivated (ha)	8.31	8.76	6.96	1.80***	6.38
Total monetary value of productive assets (CFA)	848630.80	900165.20	697231.30	202933.90***	5.73
Poverty headcount (%)	60.13	57.19	68.74	11.54***	4.86
Food insecure headcount (%)	76.59	75.15	80.82	05.67***	2.75

Source: IITA- CSAT project Mali (2019)

Moreover, the results in Table 4 does not account for other critical unobservable characteristics of the household. Therefore, any conclusion on the impact of improved agricultural technologies on any interest-based outcome on the mean differences will be biased and generate erroneous policy recommendations. Thus, the observed differences in all the outcomes between the adopters and non-adopters have no causal interpretation. Consequently, to empirically determine the impact of adopting improved agricultural technologies on all our outcomes of interest, we adopted the ESR model and that conveniently eliminates observable and unobservable biases sample and provides a consistent estimate of the impact.

4.4. Household Poverty Assessment, by Adoption Status

To assess the poverty status of the farm households, we need first to construct a poverty line. The poverty line is the threshold with which a household can be classified as either poor or non-poor. In this study, we adopted the relative poverty line computed as 2/3 of the mean per capita total household expenditure. The calculated poverty line is 72185.66 CFA/annum. We classified the farm households with per capita consumption expenditure lower than the poverty line are classified as poor households. We further used the FGT poverty assessment method to calculate all the relevant poverty indices. The results from the estimation of the FGT are presented in Table 4. The results show that poverty headcount, poverty depth, and poverty severity are higher among the non-adopters of improved agricultural technologies than the adopters. About 62 % of the non-adopter's household are living below the relative poverty line. The depth and severity of poverty are also higher among the non-adopters compare with the adopters. The results reveal that the per capita consumption expenditure of the non-adopters' households should be driven up by 39 % of its current amount if they have to be lifted out of poverty, while it takes only 26 % for the adopters. In general, the poverty headcount, depth, and severity are about 14, 13, and 11 %age point, respectively higher among the farm households that are not adopting any improved agricultural technology compare with the adopters.

Table 5: Poverty Assessment, by Adoption Status

Poverty Indices	All Households (1)	Adopters (2)	Non-adopters (3)	Percentage Point difference (3-2)
Poverty headcount	0.5149	0.4781	0.6219	0.1438
Poverty depth	0.2956	0.2622	0.3926	0.1304
Poverty severity	0.2076	0.1793	0.2899	0.1106

4.5. Endogenous Switching Regression of Determinants of Adoption of Improved Technology

The selection equation representing the determinant of a farm household's decision to adopt improved agricultural technology is presented in Table 6. The *Wald chi2(18)* of 557.48 (significant at 1% level) implies that the overall model is fitted, and the explanatory variables used in the model were collectively able to explain the farmers' decision regarding the adoption of improved agricultural technologies in Mali. Ten out of the included variables are positive and statistically significant in influencing the farm household's decision to adopt any improved agricultural technology.

The variable tropical livestock unit is considered as a proxy for farm household assets, and it is also found to have a significant and positive effect on the farmers' decision to adopt agricultural technology. Livestock such as cattle, ox, and horses are the primary means of transportation in Mali, especially for transporting inputs and farm products. Besides, they are also used as animal traction for farm operations. Consequently, a household with abundant access to this livestock could be the ones that will readily adopt new, improved agriculture technologies. The findings of some studies also confirmed that livestock holding has a significant effect on farmer's decision to adopt agricultural technology (Hasen, 2015; Kassa et al., 2014; Ketema et al., 2016). Being in a polygamous marriage is also found to have a significant and positive effect on the farmers' decision to adopt agricultural technology. Polygamous households are reported to have a large household size, which could be a source of family/unhired labour for farm activities.

The variable distance to the nearest town, is used in this study as a measure of how far the farm household is to the nearest urban market. This variable is found to have a significant and positive effect on the farmers' decision to adopt agricultural technology. A plausible explanation for this could be that those farm households far from the town (urban market in most cases) have access to large land for farming and would be able to adopt different type of technologies. This finding is however in contrast to some other studies that found that distance from the market (town) has significant and negative effect on the farm household's decision to adopt agricultural technology (Admassie and Ayele, 2010; Hagos and Zemedu, 2015).

The variable "owned bank account" is used as a proxy for savings and found to have a significant and positive effect on the farmers' decision to adopt agricultural technology. The farm household's potential to save could help to cope with various shocks and facilitate investment in technology adoption. The variable awareness/exposure to improved agriculture technologies significantly affected the farmers' decision to adopt agricultural technology. The decision to adopt or not depends on whether the farmer is 'exposed' to the technology or not. Rural farm households cannot possibly adopt a technology that is not known to them. Exposure to new technology can happen through a wide range of sources such as through the media, especially television programs, and contact with extension agents. Consequently, the variable that represents television as the primary source of information is positive and statistically significant, and it implies that the farm households whose primary source of information is through watching television are more likely to adopt improved agricultural technologies. This finding implies that the dissemination of information relating to improved agricultural technology among rural farm households is critical in establishing awareness/exposure needed for the farmers' decision to adoption any improved agricultural technology.

Overall, rural farmers are very conservative and risk-averse when trying new technologies and hence, need much time and information to be persuaded to adopt new, improved agricultural technologies (OECD, 2001). Effective campaign on innovative technologies requires dependable knowledge and practical advice that can be easily obtained by watching television programs on training and demonstration on new technologies. In the same vein, the variable 'contact with extension agents' has a positive and significant relationship with the adoption of improved agricultural technologies. This signifies the vital role of government extension services in influencing the farmers' decision to Adopt improved agricultural technologies in Mali. Several previous studies have also found similar effects of access to extension services on the farmer's decision to adopt agricultural technology (Admassie and Ayele, 2010; Ketema et al., 2016).

The farmers' main income source is positive and significantly different from zero, suggesting that the farm households whose main income comes from agriculture are more likely to adopt improved agricultural technologies than the other farm households whose primary income sources are non-agriculture. In the same vein, the variable total farm size is positive and significantly different from zero, suggesting that farm households with larger farm sizes are more likely to adopt improved agricultural technologies. Moreover, the land is also a wealth proxy variable that can positively affect the adoption of improved agricultural technologies (Feder et al., 1985). This finding is consistent with the findings of Doss and Morris (2001).

The variable membership of cooperatives also has a positive and significant relationship with adopting improved agricultural technologies. According to World Bank (2006), an agricultural cooperative's emergence is a necessary institutional arrangement that can help overcome the constraints that impede smallholders in developing countries from taking advantage of agricultural production and marketing opportunities. Several past research efforts have shown that agricultural cooperatives influence the adoption of improved agricultural technologies by farm households (Abebaw and Haile,2013; Fischer and Qaim,2012; Francesconi and Heerink,2011). In the study on Ethiopia, Abebaw and Haile (2013) find that cooperative membership exerts a positive and significant effect on fertilizer adoption. Verhofstadt and Maertens (2014) on Rwanda find a positive and significant effect of cooperative membership on the likelihood of using improved seeds, mineral fertilizer, and pesticide in the same vein. Similarly, other previous studies have also confirmed that membership to cooperatives significantly affects farmers' decision to adopt agricultural technology (Aweke, 2013; Ketema et al., 2016).

The number of years of farming experience and household size are both negative and statistically significant in determining the farm household's adoption of improved agricultural technology, suggesting that two variables reduce the probability of a farm household adopting improved agricultural technologies. This finding further suggests that the adoption of improved agricultural technologies increases with a reduction in the years of farming experience and the household size. A sizeable number of years of farming experience might be disincentive to adopting any new, improved agricultural technology. Because the rural farmers might want to continue to plant or use the same production method as they have been used to for many years. Thus, the farm households might have low acceptance for any new technology, no matter how productive it could be. The household size is a proxy for the availability of labour, and agricultural production is generally very labour intensive. Thus, a rural farm household with less access to family labour to open another land for farming or increase the farm size might choose to adopt improved technologies to maximize production from a small parcel of land.

Table 6: Endogenous Switching Regression of Determinants of Improved Technologies Adoption

Variable	**Coefficient**	**Std. Error**
Years of residence in the village	-0.002	(0.002)
Farming experience (Year)	-0.004**	(0.002
Tropical Livestock Unit(TLU)	0.0051***	(0.001)
Literacy (Yes=1)	-0.026	(0.062)
Household size (number)	-0.045***	(0.007)
Access to credit (yes=1)	0.113	(0.073)
Age of household head (Years)	0.003	(0.002)
Contact with the extension agent (Yes=1)	0.354***	(0.067)
Migrant household (Yes=1)	0.026	(0.058)
Main income source (agriculture=1)	0.211***	(0.061)
Distance to the nearest town (km)	0.002***	(0.001)

Walking distance to the nearest market (Min.)	-0.001	(0.001)
Membership of organization (Yes=1)	0.217***	(0.078)
Owned Bank account (yes=1)	0.322***	(0.105)
Total farm size (Ha)	0.011***	(0.003)
Source of information (Television=1)	0.140**	(0.061)
Married (Polygamous=1)	0.125**	(0.064)
Attended training (Yes=1)	-0.022	(0.078)
Awareness (Yes=1)	1.357***	(0.176)
Constant	-1.156***	(0.207)
Number of observations	1926.00	
Log likelihood	-25303.83	
Wald chi2(18)	557.48	
Prob > chi2	0.0000	

Note: ***, **, *, implies significant at 1%, 5% and 10%, respectively
Figures in parentheses are the Standard errors.

4.6. The Full Information Maximum Likelihood Estimates of Endogenous Switching Regression Model for Welfare and Income

The FIML estimates generated from the ESR model are presented separately in Tables 7 and 8 below. The explanation of the FIML estimates is presented in two stages. Firstly, we present the results by explaining the correlation coefficients' meaning for all the different estimations for the outcomes. The correlation coefficients are rho_1 and rho_2. The significance of the coefficient of correlation between the adoption equation, welfare, and income of adopters indicates that 'self-selection' occurred in the adoption of improved agricultural technologies. This selection bias is because of unobservable factors. Therefore, considering both observable and unobservable factors in the impact estimation is necessary to obtain an unbiased estimate of the treatment effects.

Furthermore, in the welfare and income equations, the two-correlation coefficient is observed to exhibit different signs. While the coefficient of rho_1 is positive and statistically significant at 1%, that of rho_2 is negative and not significant. This implies that the farm household's decision to adopt any improved agricultural technology is taking based on their comparative advantage. Since rho_1 is greater than zero, it suggests negative selection bias, which means that the farm households that have less than average per capita expenditure are more likely to choose to adopt improved agricultural technologies. The likelihood ratio test for joint independence of the three equations is statistically significant at 1%, and this implies that these three models are not jointly independent and should not be estimated separately. Overall, the results suggest that individual farm households that are not adopters of any improved agricultural technology have less per capita consumption expenditure and income than a random farm household from the sample. The results further reveal that if non-adopters had adopted their per capita consumption expenditure and income would have been higher. This implies that the adoption of any agricultural technology increased rural farm household welfare (measured in terms of the per capita consumption expenditure) and income. The findings of the PSM model also support these results. Secondly, the coefficients' interpretations from the outcome models of the differently estimated FIML of the ESR model are presented in the different sections below.

4.6.1. Full Information Maximum Likelihood Estimates of Welfare Equation of Endogenous Switching Regression Model

The outcome equation representing the impact of the adoption of improved agricultural technology on welfare for both adopters and non-adopters is presented in Table 7. The variable representing the years of residence in the village reveals a significant and negative impact on welfare for the adopters, but a significant and positive impact on non-adopters’ farm households' welfare. This suggests that the number of years of residence in the village is an essential determinant of improved welfare for the non-adopters’ farm households. The variable representing the tropical livestock unit shows a significant and positive impact on welfare for both adopters and non-adopters, suggesting the hat tropical livestock unit is a vital determinant of an increase in farm households' welfare.

The years of farm experience and household size have negative coefficients and are statistically significant in explaining the variation in per capita consumption expenditure among the farm households adopting improved agricultural technologies. Large household size has been identified as a significant contribution to poverty among the rural farming households in Nigeria (Omonona and Okunmadewa, 2009). Therefore, the larger the household size, the greater the probability of being poor and the lesser the availability of resources for household expenditure, and hence there is more likelihood of reduced welfare. In the same vein, the total farm size, age of household head, contact with extension agent, migration, married (polygamous), distance to the nearest town, and distance to the nearest market have positive and statistically significant relationship with the per capita consumption expenditure among the non-adopter households.

Furthermore, for the non-adopters’ households, household size and having at least one migrant from the household is negative and statistically significant in explaining the variation in per capita consumption expenditure among the non-adopting households. However, the years of residence in the village, total farm size, age of household head, married (polygamous), and distance to the nearest town have a positive and statistically significant relationship with the per capita expenditure. The differences in the coefficient of the consumption expenditure equation for the farm households that adopted improved agricultural technology and those that did not adopt reveal heterogeneity in the sample. The farm households' consumption expenditure function that adopted is significantly different (at 1%) from the consumption expenditure function of the farm households that did not adopt.

Table 7: Full Information Maximum Likelihood Estimates of Welfare Equation of Endogenous Switching Regression Model

Variable	Coefficient	Std. Error	Coefficient	Std. Error
	Adoption=1		Adoption=0	
Years of residence in the village	-387.392**	(152.534)	485.797**	(218.018)
Attended training (Yes=1)	-15766.830**	(6458.079)	7800.836	(13015.3)
Farming experience (Year)	-316.594*	(181.269)	-280.721	(276.245)
Tropical livestock unit (TLU)	846.219***	(139.528)	493.892***	(173.131)
Literacy (Yes=1)	-1781.508	(5506.976)	7008.911	(9043.154)
Total farm size (Ha)	1455.690***	(261.132)	575.397	(386.004)
Household size (number)	-6793.527***	(480.480)	-5359.65***	(760.474)
Source of information (Television=1)	19302.560***	(5464.115)	13888.64	(9744.622)
Access to credit (yes=1)	8473.749	(6467.487)	15569.5	(11459.36)
Age of household head (Years)	564.285**	(227.361)	84.916	(331.585)
Contact with the extension agent (Yes=1)	27635.07***	(6581.686)	-21306.17**	(9818.139)
Migrant Household (Yes=1)	4091.404	(5339.588)	11899.94	(8319.207)
Main income source (agriculture=1)	26766.64***	(5599.312)	-18094.48**	(8602.399)
Married (Polygamous=1)	13472.63**	(5818.09)	20285.73**	(9243.174)
Distance to the nearest town (km)	201.447***	(59.894)	60.91026	(121.700)
Walking distance to the nearest market (Min.)	-95.10755	(115.399)	11.561	(145.989)
Membership of organization (Yes=1)	35534.93***	(7335.716)	-7167.323	(9210.922)
Owned Bank account (yes=1)	36126.97***	(8335.201)	34099.42**	(15098.43)
Constant	6046.076	(14705.140)	59880.26***	(21292.38)
/lns1	11.574	(0.019)		
/lns2	11.338	(0.042)		
/r1	2.461	(0.155)		
/r2	-0.2757991	(0.196)		
sigma_1	106280.7	(2092.395)		
sigma_2	83954.42	(3501.281)		
rho_1	0.986***	(0.004)		
rho_2-non-adopters	-0.269	(0.182)		
LR test of indep. eqns.:	chi2(1) = 970.11	Prob > chi2 = 0.0000		

Note: Figures in parentheses are the Standard errors.
***, **, *, implies significant at 1%, 5% and 10%, respectively.

4.6.2. Full Information Maximum Likelihood Estimates of Per Capita Household Income Equation of Endogenous Switching Regression Model

The outcome equation representing the impact of adoption of improved agricultural technology on the per capita households' income for both adopters and non-adopters is presented in Table 8. The results show that household characteristics and institutional factors have differential impact among the adopter and non-adopters of improved agricultural technology. Having agriculture as a main source of income, tropical livestock unit, total farm size, obtaining information through television, access to credit, contact with the extension agent, distance to the nearest town, membership of organization and owned Bank account (proxy for savings) are all positive and statistically significant in determining income among the adopter's households. On the other hands, in the case of the non-adopters' households, their income is only positively and statistically influenced by the tropical livestock unit, total farm size, distance to the nearest town and owned Bank account (Proxy for savings). The number of years of residence in the village and household size are both negative and statistically significant in determining the income for both adopters and non-adopters' households. This implies that households' income for the adopters and non-adopters decrease with increase in these variables. In addition, walking distance to the nearest market affect both the adopters and non-adopters' households' income negatively, but it is only significant for the non-adopters farm households.

Table 8: Full Information Maximum Likelihood Estimates of Total Household Income Equation of Endogenous Switching Regression Model

	Coefficient	Std. Error	Coefficient	Std. Error
Variable	Adoption=1		Adoption=0	
Years of residence in the village	-208.759*	(117.858)	-370.333***	(130.583)
Attended training (Yes=1)	-8092.157	(4977.019)	2319.785	(7794.683)
Main income source (agriculture=1)	29563.71**	(4310.481)	-914.873	(5216.698)
Farming experience (Year)	120.3561	(139.417)	-3.472	(165.473)
Tropical livestock unit	640.6817***	(106.408)	396.246***	(103.158)
Literacy (Yes=1)	4166.385	(4242.116)	2809.185	(5423.715)
Total farm size (Ha)	1145.108***	(201.004)	1024.952***	(231.041)
Household size (number)	-4537.778***	(369.342)	-2830.758***	(451.539)
Source of information (Television=1)	15378.2***	(4200.677)	419.643	(5726.183)
Access to credit (yes=1)	21417.14***	(4975.198)	518.039	(6893.961)
Age of household head (Years)	-217.8066	(175.272)	77.619	(198.933)
Contact with the extension agent (Yes=1)	27009.47***	(5051.445)	-1513.794	(5635.058)
Migrant Household (Yes=1)	-156.5534	(4116.636)	-2054.602	(4909.38)
Married (Polygamous=1)	-699.8222	(4485.073)	523.371	(5413.36)
Distance to the nearest town (km)	234.6473***	(46.026)	135.387*	(73.513)
Walking distance to the nearest market (Min.)	-44.70905	(87.622)	-147.024*	(86.822)
Membership of organization (Yes=1)	23287.11***	(5661.695)	3857.244	(5330.829)
Owned Bank account (yes=1)	12675.45**	(6405.115)	22308.36**	(8829.29)
Constant	2489.207	(11297.43)	51845.88***	(12675.50)
/lns1	11.316	(0.019)		
/lns2	10.813	(0.035)		
/r1	2.617	(0.155)		
/r2	-0.149	(0.147)		
sigma_1	82088.03	(1599.173)		
sigma_2	49672.47	(1719.608)		
rho_1	0.9893832***	0 .0032653		
rho_2	-0.1480214	0 .1435421		
LR test of indep. eqns. :	chi2(1) = 989.90	Prob > chi2 = 0.0000		

Note: Figures in parentheses are the Standard errors.

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

4.6.5. Endogenous Switching Regression-Based Treatment Effects for Welfare and Income

The expected values of the welfare and household income under the actual and counterfactual situations and the resulting treatment effects are presented in Table 11. The ESR-based treatment effects show that improved agricultural technology positively and significantly impacts the farm household's welfare and per capita household income. The expected per capita expenditure (welfare) and income for the farm households that adopted improved agricultural technology are 126504 CFA and 88959 CFA, respectively, while it is -43539.63CFA -48500.49 CFA, respectively for those who did not. In the counterfactual case, the farm households who adopted the improved agricultural technology would have obtained a per capita consumption expenditure and income of 58828 CFA and 40610.81CFA, respectively, had they decided not to adopt. Therefore, the adoption of improved agricultural technology had significantly increased the adopters' per capita consumption expenditure and income by 67638 CFA and 48347.79 CFA, respectively.

In the counterfactual case, the farm households that did not adopt any improved agricultural technology would have had their per capita consumption expenditure and income increased by 127382.4 CFA and 89683.69 CFA, respectively, had they adopted any improved agricultural technology. This positive effect on welfare and income is expected because adopting any improved agricultural technology would help the farm households have higher productivity, leading to a higher marketable surplus and a resultant increase in household income that can be used to improve the household's consumption expenditure/welfare.

Table 9: Endogenous Switching Regression-Based Treatment Effects

Outcome variables	**Household type and treatment effects**	**Decision Stage**		ATEs
		To use	**Not to use**	
Welfare (per capita expenditure) (CFA)	Adopter farm households (ATET)	126503.8	58828.1	67637.75(825.12)***
	Non-adopters farm households (ATUT)	83978.08	-43539.63	127382.4(2710.69)***
	Heterogenous effects	42,525.72	102,367.7	-59,744.65
Per capita household income(CFA)	Adopter farm households (ATET)	88958.6	40610.81	48347.79(466.78)***
	Non-adopters farm households (ATUT)	41183.2	-48500.49	89683.69(1497.24)***
	Heterogenous effects (HE)	47775.40	89111.30	-41,335.90

***, **, *, implies significant at 1%.

The positive based heterogeneity effect for the welfare and per capita income implies that improved agricultural technology adopters have higher welfare and income possibly as a result of their decision to adopt improved agricultural technology. The negative transitional heterogeneity effect also suggests that the effect of adopting improved agricultural technology would be higher for the non-adopter households had they decided to adopt.

4.6.3. Determinants of Poverty-ESPR

The estimated parameters for the endogenous switching probit (ESP) model, revealing the factors that influence the farm households' poverty status, are presented in table 10. The result shows that poverty headcount is reduced significantly among the farm households that adopted improved agricultural technology by the total farm size, TLU, access to information through television, owned Bank account (a proxy for savings), having at least one household member that have migrated. Besides, access to credit reveals a negative but not statistically significant relationship with adopters' household poverty status. In the same vein, poverty among non-adopting households is reduced by the number of years of residence in the village, access to information through television, access to credit, TLU, and having at least one household member have migrated.

Table 10: Impact of Adoption of Improved Agricultural Technologies on Poverty-ESPR

	Coefficient	Std.Error	Coefficient	Std.Error
Variable	**Adoption=1**		**Adoption=0**	
Years of residence in the village	0.005***	(0.002)	-0.008**	(0.003)
Attended training (Yes=1)	0.124	(0.079)	0.020	(0.207)
Farming experience (Year)	-0.002	(0.002)	0.005	(0.004)
Age square	-0.000	(0.000)	-0.000	(0.000)
Literacy (Yes=1)	0.123*	(0.071)	-0.043	(0.146)
Total farm size (Ha)	-0.010***	(0.003)	-0.008	(0.006)
Source of information (Television=1)	-0.161**	(0.073)	-0.270*	(0.143)
Access to credit (yes=1)	-0.019	(0.084)	-0.495***	(0.178)
Age of household head (Years)	0.003	(0.014)	0.026	(0.026)
Distance to the nearest town (km)	-0.000	(0.001)	-0.002	(0.002)
Walking distance to the nearest market (Min.)	0.001	(0.002)	-0.002	(0.002)
Membership of organization (Yes=1)	-0.028	(0.103)	-0.005	(0.155)
Tropical livestock unit	-0.009***	(0.002)	-0.008***	(0.003)
Migrant Household (Yes=1)	-0.114*	(0.068)	-0.265**	(0.126)
Contact with the extension agent (Yes=1)	0.091	(0.108)	0.010	(0.187)
Married (Polygamous=1)	-0.009	(0.074)	-0.179	(0.146)
Owned Bank account (yes=1)	-0.498***	(0.104)	-0.043	(0.225)
Constant	0.327	(0.465)	0.716	(0.732)
/athrho1	0.466**	0.222		
/athrho0	-0.213	0.251		
rho1	0.435**	0.180		
rho0	-0.210	0.240		
LR test of indep. eqns. (rho1=rho0=0):chi2(2) =	5.16 Prob > chi2 = 0.0756			

Note: Figures in parentheses are the Standard errors.

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

4.6.4. Determinants of Food Insecurity-ESPR

The estimated parameters for the ESP model, revealing the factors that affect the farm households' food insecurity status, are presented in table 11. The most critical and policy-relevant variables influencing food insecurity among the rural farm households significantly reduce food insecurity. The results reveal that the years of farming experience, the age square of the households' head, having television as the main Source of information, access to credit, walking distance to the nearest market, and being in a polygamous marriage. Meanwhile, among the non-adopter farm households, food insecurity is decreased by the number of years of residence in the village, having television as the main Source of information, and tropical livestock unit.

Table 11: Impact of Adoption of Improved Agricultural Technologies on Food Insecurity-ESPR

	Coefficient	**Std. Error**	**Coefficient**	**Std. Error**
Variable	**Adoption=1**		**Adoption=0**	
Years of residence in the village	-0.003	(0.002)	-0.006*	(0.003)
Attended training (Yes=1)	0.029	(0.084)	0.445**	(0.203)
Farming experience (Year)	-0.008***	(0.002)	0.005	(0.004)
Age square	-0.000***	(0.000)	-0.000	(0.000)
Literacy (Yes=1)	0.109	(0.075)	0.019	(0.148)
Total farm size (Ha)	0.000	(0.004)	0.017**	(0.007)
Source of information (Television=1)	-0.358***	(0.083)	-0.511***	(0.159)
Access to credit (yes=1)	-0.326***	(0.095)	-0.213	(0.180
Age of household head (Years)	0.044***	(0.015)	0.001	(0.026)
Distance to the nearest town (km)	-0.000	(0.001)	-0.000	(0.002)
Walking distance to the nearest market (Min.)	-0.003**	(0.002)	-0.003	(0.002)
Membership of organization (Yes=1)	0.256**	(0.103)	0.201	(0.151)
Tropicall livestock unit(TLU)	-0.002	(0.002)	-0.007***	(0.003)
Migrant Household (Yes=1)	-0.016	(0.072)	-0.183	(0.129)
Contact with the extension agent (Yes=1)	0.294***	(0.108)	0.078	(0.169)
Married (Polygamous=1)	-0.181**	(0.081)	0.111	(0.146)
Owned Bank account (yes=1)	0.058	(0.108)	-0.189	(0.217)
Constant	-0.383	(0.467)	1.514**	(0.739)
/athrho1	0.626	(0.241)		
/athrho0	(0.686)	(0.304)		
rho1	(0.555)***	(0.167)		
rho0	(0.596)***	(0.196)		
LR test of indep. eqns. (rho1=rho0=0):chi2(2) = 12.06 Prob > chi2 = 0.0024				

4.6.5. Endogenous Switching Probit-Based Treatment Effects for Poverty and Food Insecurity

The estimates of the ATET, which show the impact of adoption on poverty and food security status after accounting for both observable and unobservable characteristics, are presented in Table 12. The results reveal that both adopters and non-adopters benefit from the adoption of improved agricultural technology. Specifically, the probability of being poor and food insecure from adopting households would be 4% and 20 % more, respectively, had the households not adopted any improved agricultural technology. This is the ATET, which is statistically significant at the 1% confidence level. Similarly, the probability of being poor and food insecure would have been 34 % and 36 % less, respectively, had the non-adopting farm households adopted any improved agricultural technology. This implies that the non-adopting farm households would have reduced poverty headcount rates and food insecurity if they had shifted from non-adopting to adopting any improved agricultural technology under the given conditions. This is the average treatment effect on the untreated (ATUT) which is also statistically significant and implies that non-adopting households would be better off (less poor and more food secure) if they had adopted any improved agricultural technology.

Table 12: Endogenous Switching Probit-based Treatment Effect for Poverty and Food Insecurity

Outcome variables	**Treatment Effect**	**Average Treatment Effects (ATEs)**
Poverty headcount (%)	Farm households that adopted (ATET)	-0.04(0.003)***
	Farm households that did not adopt (ATUT)	-0.34(0.006)***
Food insecurity headcount (%)	Farm households that adopted (ATET)	-0.20(0.003)***
	Farm households that did not adopt (ATUT)	-0.36(0.006)***

***, implies significant at 1%.

4.7. Propensity Score Matching (PSM)

The ESR models' results are sensitive to the exclusion restriction assumption; hence, we also used the PSM approach to check the robustness of the estimated effects obtained from the ESR models. We also used the same variables in the estimation of the propensity scores. A visual inspection (figure 2) of the density distributions of the estimated propensity scores for the adopters and non-adopters indicates that the common support condition is satisfied. There was a substantial overlap in the distribution of the propensity scores of both adopter and non-adopter groups. The bottom half of the graph shows the distribution of propensity scores for the non-adopters, and the upper half refers to the adopters.

The effect of improved agricultural technology adoption on welfare, income, and poverty headcount was estimated with the Nearest Neighbour (NNM) and the Kernel-Based (KBM) matchings. Tables 12-14 presents the results of the ATT estimates from the PSM approach. The NNM and KMB results show a positive and significant Average Treatment Effect on the Treated (ATET) of 27643.58 CFA and 25960.21CFA for the NNM and KBM, respectively. The ATET is the effect of adopting improved agricultural technology on per capita consumption expenditure (a proxy for welfare). It is the average difference between the per capita consumption expenditure of similar pairs of rural farm households but belonging to different adoption status. Similarly, the Average Treatment Effect (ATE), which gives the average effect of adoption on per capita total consumption expenditure for a rural farm household drawn from the overall population at random, is 25642.27 CFA and 23841.92 CFA for the NNM and the KBM, respectively. Besides, the adoption of improved agricultural technologies can increase the per capita total consumption expenditure of the rural farm households by between 48%- 66%.

Furthermore, the total household income for the adopters is statistically and significantly higher than the non-adopters by more than 29,000 CFA. Adoption of improved agricultural technologies is revealed to contribute between 29-36 % increase in per capita total income of the adopting rural farm households. The increase in total household income is assumed to lead to the reduction in poverty headcount among the rural farm households. Consequently, the PSM results further show that the adoption of improved agricultural technologies has the potential to significantly reduce poverty by between 10.27 % and 10.31 %.

Table 12: Effect Adoption of Improved Agricultural Technology on Welfare

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Nearest Neighbour Matching (NNM)						
Per capita consumption expenditure (₦)	Unmatched	116700.582	84236.339	32464.24	5410.059	6.00
	ATT	116700.582	89056.998	**27643.58*****	7794.562	3.55
	ATU	84236.339	104007.571	19771.23	-	-
	ATE			25642.27	-	-
	Impact (%)			0.66***		
Kernel Based Matching (KBM)						
Per capita consumption expenditure(₦)	Unmatched	116700.582	84236.339	32464.24	5410.059	6.00
	ATT	116700.582	90740.368	**25960.21*****	6367.861	4.08
	ATU	84236.339	101864.032	17627.69	-	-
	ATE			23841.92	-	-
	Impact (%)			0.48***		

Table 13: Effect Adoption of Improved Agricultural Technology on Per Capita Total Income

Variable	Sample	Treated	Controls	Difference	S.Error	T-stat
NNM						
Per Capita Total Income (₦)	Unmatched	81342.372	42012.657	39329.715	3994.785	9.85
	ATT	81342.372	51735.136	**29607.236*** **	5209.667	5.68
	ATU	42012.657	67028.788	25016.130	-	-
	ATE			28440.085	-	-
	Impact (%)			0.36***		
KBM						
Per Capita Total Income (₦)	Unmatched	81342.372	42012.657	39329.715	3994.785	9.85
	ATT	81342.372	51424.849	**29917.523*** **	4066.011	7.36
	ATU	42012.657	66380.842	24368.185	-	-
	ATE			28506.770	-	-
	Impact (%)			0.29***		

Table 14: Effect Adoption of Improved Agricultural Technology on Poverty Headcount

Variable	Sample	Treated	Controls	Difference	S.Error	T-stat
NNM						
Poverty Headcount (%)	Unmatched	0.58	0.70	-0.1227	0.0252	-4.87
	ATT	0.58	0.68	**-0.1027** **	0.0378	-2.72
	ATU	0.70	0.62	-0.0783	.	.
	ATE			-0.0965	.	.
KBM						
Poverty Headcount (%)	Unmatched	0.58	0.70	-0.1227	0.0252	-4.87
	ATT	0.58	0.68	**-0.1031*** **	0.0307	-3.36
	ATU	0.70	0.64	-0.0561	.	.
	ATE			-0.0912	.	.

5.0. Summary, Conclusion and Policy Recommendations

The paper assesses the impact of adopting improved agricultural technology on welfare, poverty, and food security in rural Mali. The study utilizes cross-sectional farm household-level data collected in 2019 from a randomly selected sample of 2240 in four regions and 32 communes in Mali. We estimate the causal impact of improved agricultural technologies adoption by utilizing the endogenous switching regression model to control for selection bias and endogeneity due to the respondents' observable and unobservable characteristics and adopted the PSM method to assess the robustness of the estimates of the impacts. The causal impact estimation from both the ESR and PSM models suggests the adopters of improved agricultural technologies have significantly higher per capita expenditure (welfare) and income than the non-adopters. Also, poverty headcount and food insecurity are significantly lower among the adopters compare to the non-adopters.

In conclusion, the analyses suggest that the adoption of improved agricultural technologies contributes significantly to improving rural household welfare and reducing food insecurity and poverty. The results also show that the adoption of improved agricultural technologies could be increased by raising awareness, providing frequent extension visits, improving agricultural information systems, and enhancing rural farmers' participation in agricultural events/training. Therefore, the implication of these is that any policy that will increase rural households' welfare, reduce poverty and food insecurity among the rural farm households should promote improved agricultural technologies.

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Appendix A

Table: Test of balancing

	Mean			t-test	
Variable	**Treated**	**Control**	**%bias**	**t**	**p>t**
Years of residence in the village	56.932	57.481	-2.6	-0.39	0.697
Attended training (Yes=1)	0.103	0.127	-6.1	-1.19	0.233
Farming experience (Year)	41.016	40.517	2.8	0.44	0.663
Tropical livestock unit(TLU)	13.395	14.447	-4.9	-0.77	0.441
Literacy (Yes=1)	0.237	0.278	-8.6	-1.45	0.147
Total farm size (Ha)	11.506	12.038	-5.1	-0.86	0.392
Household size (number)	8.018	7.742	5,0	0.66	0.510
Source of information (Television=1)	0.266	0.298	-6.7	-1.13	0.260
Access to credit (yes=1)	0.117	0.165	-11.3	-2.19	0.029
Age of household head (Years)	57.664	57.978	-2.1	-0.32	0.749
Contact with the extension agent (Yes=1)	0.485	0.483	0.4	0.06	0.949
Migrant (Yes=1)	0.469	0.467	0.4	0.06	0.949
Main income source (agriculture=1)	0.390	0.451	-12.3	-1.93	0.054
Married (Polygamous=1)	0.682	0.696	-3.1	-0.48	0.632
Distance to the nearest town (km)	16.458	18.762	-5.4	-1.29	0.198
Walking distance to the nearest market (Min.)	14.266	14.547	-1.1	-0.18	0.855
Membership of organization (Yes=1)	0.688	0.666	5.3	0.75	0.456
Age square	3569.30	3593.50	-1.4	-0.21	0.833
Bank account (yes=1)	0.076	0.089	-3.7	-0.69	0.490

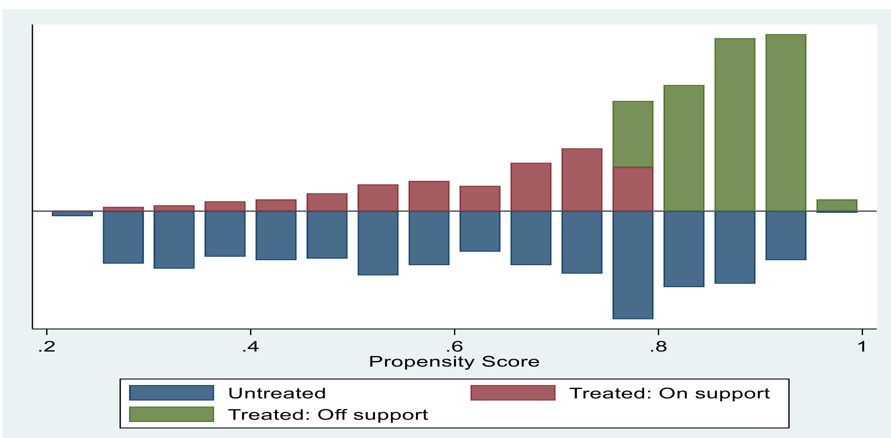

Figure 2: Propensity score distribution and common support for propensity score estimation.
Note: “Treated: on support” implies the observations in the adoption group that have a suitable comparison. “Treated: off support” indicates the observations in the adoption group that do not have a suitable comparison.