IOCAG 2022

Proceedings

Evaluating the Heterogeneous Impacts of Adoption of Climate-Smart Agricultural Technologies on Rural Household Welfare in Mali †

Bola Amoke Awotide [1,*], Adebayo Ogunniyi [2], Kehinde Oluseyi Olagunju [3], Lateef Olalekan Bello [4], Amadou Youssouf Coulibaly [5] and Alexander Nimo Wiredu [6]

[1] International Institute of Tropical Agriculture (IITA), Bamako, Mali
[2] International Fund for Agricultural Development (IFAD), Abuja, Nigeria;
[2] Economics Research Branch, Agri-Food and Biosciences Institute, 18a Newforge Lane, Belfast BT9 5PX, UK
[4] Department of Global Agricultural Science, The University of Tokyo, Bunkyo-Ko, Tokyo 113-8657, Japan
[5] Institut de Pedagogie Universitaire (IPU), Bamako, Mali
[6] International Institute of Tropical Agriculture (IITA), Nampula, Mozambique
* Correspondence: B.Awotide@cgiar.org/bawotide@yahoo.com; Tel.: +223-75012525
† Presented at the 1st International Online Conference on Agriculture-Advances in Agricultural Science and Technology (IOCAG2022), 10–25 February 2022; Available online: https://iocag2022.sciforum.net/.

Abstract: This article investigates the distributional impacts of the adoption of Climate-Smart Agricultural Technologies (CSAT) on farm households' welfare using a dataset that covers four regions, 32 communes, 320 villages and 2240 households in Mali. Using an instrumental variable quantile treatment effects model, the paper addresses the potential endogeneity arising from the selection bias and the heterogeneity of the effect across the quantiles of the outcome variables' distribution. The results show that the adoption of CSAT is positively associated with improved households' welfare and the farmer decision to adopt any CSAT is positively and statistically influenced by access to credit, contact with extension agents, participation in training, access to information through the television and being a member of any organization such as cooperative society. Moreover, the results further show that the effect of adoption of CSAT on household welfare varied across the different households. In particular, the results show that the impact of adoption of CSAT on households' welfare is generally higher for the poorest (farmers located at the bottom tail of the distribution) end of the welfare distribution. The findings, therefore, highlight the pro-poor impact of the adoption of CSAT in the rural Malian context, as well as the need to tailor the CSAT interventions toward specific socio-economic segments of the rural population in Mali.

Keywords: climate-smart agricultural technologies; quantile regression; endogeneity; Sahel region; Mali

JEL Classification: C13, C14, C30, C51

Citation: Awotide, B.A.; Ogunniyi, A.; Olagunju, K.O.; Bello, L.O.; Coulibaly, A.Y.; Wiredu, A.N. Evaluating the Heterogeneous Impacts of Adoption of Climate-Smart Agricultural Technologies on Rural Household Welfare in Mali. *Chem. Proc.* **2022**, *4*, x. https://doi.org/10.3390/xxxxx

Academic Editor(s):

Published: date

1. Introduction

The global population is rapidly growing, and it exceeded 7.6 billion people in 2018 (United Nations, 2019). It is also predicted to reach 9.2 billion by 2050 (Silva, 2018), with a projected increase in food demand of 59–102% (Elferink and Schierhorn, 2016; Fukase and Martin (2017). Efforts to increase agricultural productivity by 60–70% seem to be highly necessary to provide food for the population in 2050 (Silva, 2018). Agricultural productivity growth is one of the most critical and effective pathways for agricultural research and technologies to increase rural incomes and reduce poverty (Gollin, Hansen, and Wingender, 2018). Studies have shown that agricultural growth has a more considerable effect on reducing poverty than growth in any other sector (de Janvry and Sadoulet, 2010; Ravallion Datt, 1996; Warr, 2003). Increasing agricultural productivity through adoption and diffusion of modern agricultural technologies is recognized as one of the key pathways for economic and agricultural transformation in developing countries (Evenson and Gollin 2003; Gollin 2010). Consequently, consistent efforts from national governments and development parastatals have been devoted to developing and disseminating climate-smart agricultural technologies, particularly in regions experiencing huge adverse effects of climate change.

Sub-Saharan Africa (SSA) remains the world's most food-insecure region, with almost one-fourth of people—over 230 million—being undernourished (FAO et al., 2019). Although agriculture occupies a vital position in the economies of most SSA regions, it is mainly rainfed (Mendelsohn, and Dinar, 2009; Seo, Mendelsohn, Dinar, Hassan, and Kurukulasuriya, 2009; Wani, Sreedevi, Rockstrom, and Ramakrishna, 2009). Thus, highly susceptible to climate change effects (Brooks, Adger, and Kelly, 2005), worsening the already terrible poverty and food insecurity situations of the large majority of the rural households whose livelihood and survival depend solely on agriculture (World Bank, 2016).

In addition, agricultural yields in Africa are among the lowest in the world. In the 1960s, for instance, the average cereal yield in Africa puts at 57% of the world is among the lowest. Similarly, by the 1980s and 1990s, the yield gap had widened, with Africa achieving a cereal yield of only 47% compared to the rest of the world. According to Dzanku et al. (2015), the situation may likely remain the same as in the 1990s and may probably get worse in the face of climate change if no appropriate action/intervention is taking. The future projections based on observed climate trends indicate that temperatures in SSA are consistently rising at an alarming rate than the global average increase during the 21st century (Christensen, Carter, Rummukainen, and Amanatidis, 2007; James and Washington, 2013; Joshi, Hawkins, Sutton, Lowe, and Frame, 2011; Sanderson, Hemming, and Betts, 2011). Therefore, it is most likely that SSA might be strongly affected by climate change. Furthermore, Africa's agrarian economies are likely to disproportionately bear the burden of substantial agricultural yield losses (Dinar, Hassan, Mendelsohn, and Benhin, 2012; Solomon et al., 2007).

The present situation in the Sahelian regions of Africa in the face of erratic climate change effects is highly problematic. The incidence of drought and floods in this region is becoming more severe and frequent over time. Several factors have been identified to be responsible for the vulnerability to climate change in the Sahel. Notably among these factors is the pervasiveness of poverty that reduces the resources with which affected communities, households, and individuals can adapt to and recover from climate events. Other factors are the over-reliance of majority of the population [80–90% (UNEP, 2012)] on farming and pastoralism, linked intimately to weather trends and environmental conditions. Thus, implying that climate change effects can jeopardize the livelihood and food security of the Sahelian rural households.

The Republic of Mali is a notable country in the Sahelian region of West Africa. Being a landlocked country, Mali appears to be negatively more affected by climate change, especially agricultural production reduction, which can further increase the prevalence of poverty, hunger, and food insecurity and further undermine the welfare of the smallholders in particular and the population in general. Thus, there is a great need to concentrate on agricultural technologies capable of mitigating the adverse effects of climate change, particularly on smallholder rural farm households. The Climate Smart agriculture (CSAT) concept was proposed by the Food and Agriculture Organization of the United Nations (FAO) at the Hague Conference on Agriculture, Food Security and Climate Change in 2010. Climate-Smart Agriculture (CSAT) is an approach to agricultural Development that aims to address the intertwined challenges of food security and climate change (Lipper et al., 2014). It is built upon three pillars: increase agricultural productivity and incomes, adapt and build resilience to climate change within the agricultural systems, and reduce Green House Gas (GHG) emissions, when possible, through CSAT programs promotion of different technologies, practices and policies involve diverse institutions and investments. These interventions take place at field, farm, regional and national level (FAO, 2012). Therefore, the adoption of climate-smart agricultural technologies is view as a way out of the adverse effects of climate change on agricultural productivity, particularly in the Sahel region of West Africa.

Large piece of evidence from the literature show that adopting agricultural technologies in developing economies contributes to increased farm productivity and reduces household poverty (e.g., Khonje et al., 2014; Zeng et al., 2015). Concerning CSAT practices, there exists an extensive literature on adoption impacts of individual climate-smart practices, although with divergent findings (e.g., Di Falco and Chavas 2009; Kato et al., 2011; Di Falco and Veronesi 2013; Abdulai and Huffman 2014; Zougmore et al. ,2014; Ng'ombe et al., 2017). Adopting climate-smart agriculture can also increase crop productivity, improve farm household security in food and nutrition, and decrease crop failure (e.g., Kato et al., 2011; Di Falco and Veronesi 2013; Abdulai and Huffman 2014). However, the World Bank (2009) reported decreased revenue from plots where farmers have adopted soil conservations practices, such as the use of stone bunds in Burkina Faso. In contrast, Nkala et al. (2011) find no significant effect of minimum tillage on household incomes in Mozambique.

Furthermore, Di Falco and Chavas (2009) reported that biodiversity positively affects risk reduction among barley producers in Ethiopia. The study by Di Falco and Veronesi (2013) also reveals that adaptation to climate change, through the adoption of soil conservation, changing crop varieties, switching from early to late planting, and other practices, generate an increase in maize yield among the adopter farm households in Ethiopia. However, other studies have shown that soil conservation, crop choice, and other practices can increase technical efficiencies among farmers and minimize on-farm environmental damage (Solis et al., 2007; Veettil et al., 2017; Sabiha et al. ,2017). The results from these studies have also been mixed and inconclusive. In addition, many of these studies only investigate the effect of CSAT on mean yield, mean income and expenditure. This general result only implies that adoption of CSAT tends to have a statistically significant positive impact on the income and total household expenditure of the ''average'' (or the mean income/expenditure) farmer. This finding does not give specific information on whether (and how much) CSAT adoption affects the income, consumption expenditure at the lower or upper end of the distribution. This suggests a gap in the literature about the potential heterogeneity impact of adoption of CSAT. More importantly, the overarching question is whether the adoption of CSAT has a heterogeneous impact on the households at different points of the income and total household expenditure distribution? Of great importance in many areas of empirical economic research is the ability to understanding or provide answers to the effect of any intervention on the distribution of outcomes.

Overall, policymakers in developing countries would be more interested in supporting increased adoption of CSAT if there is empirical evidence that the lower-welfare farmers (who are typically poor smallholders) specifically benefit from CSAT adoption. Understanding the effects of CSAT adoption at different points of the welfare distribution would provide a more detailed insight into the economic impacts of CSAT adoption. Suppose adoption of CSAT has a statistically significant effect on the higher end of the welfare distribution but reveals no or negative impact for the lower welfare/poor smallholder farmers. If that is the case, it therefore, suggests that investing in the development, dissemination, and promotion of the CSAT is not a good policy option, especially in cases where the priorities are an increase in farm productivity and households' welfare. Furthermore, if on the other hand we discovered that adoption of CSAT significantly impacts the productivity, income, and expenditure (welfare) of the farm households in the lower tail of the distribution, it therefore, suggests that promoting the adoption of CSAT among the resource-poor smallholder farmers may be a practical action, and further suggests that it could increase the poor smallholders' income, increase agricultural productivity, and improve the overall farm household welfare.

In this study, the primary motivation is the estimation of the overall impact of the adoption of CSAT on income and household welfare and the heterogeneous effects on the farm household's welfare. The study, seeks to fill these gaps by addressing the following research questions: What determines households' decision to participate in the adoption of CSAT? What is the overall collective impact of the adoption of CSAT on income and household welfare? Based on findings from these previous studies, it implies that observably both lower-yielding and higher-yielding farmers in developing countries equally benefit from the adoption of CSAT. Given that developing country farmers at the lower end of the yield distribution tend to be poorer than those at the upper end. These previous studies also suggest that the benefits of CSAT adoption would be felt by all types of farmers regardless of whether they are poor smallholders or larger commercial producers.

One way to capture the effects of CSAT adoption at different points of the welfare distribution is to use quantile regression techniques introduced by Koenker and Bassett (1978). This technique has been used in various studies in applied economics to study the effects of regressors at different points of a particular outcome distribution, mainly in studying wage distribution or trade effects (see Bishop et al., 2005; Falaris, 2008; Yasar et al., 2006). However, if there are endogeneity or self-selection problems, the coefficient estimates from standard quantile regression techniques may be biased (Melly, 2006; Wehby et al., 2009; Chernozhukov and Hansen, 2004). Moreover, the standard instrumental variable (IV) or two-stage least squares (2SLS) approach in ordinary least squares (OLS) regression is not directly applicable in a quantile regression context. Chen and Portnoy (1996) developed a quantile regression analog to the standard 2SLS approach called a two-stage quantile regression (2SQR). However, Chernozhukov and Hansen (2004) show that 2SQR is inconsistent when the quantile treatment effect differs across quantiles.

Chernozhukov and Hansen (2004, 2005, 2006) developed an IV technique applicable for quantile regressions (called the instrumental variable quantile regression or IVQR) to address this problem. They have shown that the estimated coefficients in this approach are unbiased. Only a few studies have applied IVQR in empirical settings (e.g., Atella et al., 2008; Wehby et al., 2009; Olagunju et al., 2019). To the best of our knowledge, the estimation of the possible heterogeneous effects of CSAT adoption on different points of the welfare distribution, especially in the presence of self-selection (i.e., non-random selection of CSAT adopters) is still not a well-researched area, particularly for the Sahelian region of West Africa. Thus, a gap is still currently existing in the literature. Therefore, contributing to the literature by filling this gap is one of the primary motivations for this study. Specifically, we seek to determine the effect of CSAT adoption at different points of the welfare distribution. To achieve this objective, we adopted the Instrumental Variable Quantile Regression (IVQR) of Chernozhukov and Hansen (2005) and Chernozhukov and Hansen (2008) to identify the quantile treatment effect. Explicitly, the instrumental variable quantile regression model (Chernozhukov and Hansen, 2005, 2013) aims to investigate heterogeneous treatment effects in the presence of an endogenous binary treatment variable.

2. Methodology

Conceptual Framework and Estimation Strategy

The current and future impacts of climate change are a major source of concern in Sub-Saharan Africa (SSA), due to predominance of rain-fed subsistence-oriented agriculture in the region. (Mendelsohn and Dinar, 2009; Seo, Mendelsohn, Dinar, Hassan, and Kurukulasuriya, 2009). The region is affected both by extreme weather events and by long-run climate variability, which can severely reduce yields and increase the levels of uncertainty with respect to agricultural production and output prices, leading to an overall increase welfare vulnerability of smallholders (IPCC, 2014). The treatment variable in this study is adoption of Climate-Smart Agricultural Technology (CSAT).

The broad definition of CSAT includes the integration of different farming/agronomic practices and systems, as well as the improvement of input use, such as seeds, pesticides, water, etc. It includes typical technologies like climate stress tolerant seed, irrigation, and fertilizer, which are classic examples in technology adoption studies (Simtowe and Zeller, 2006; Abate et al., 2016) as well as practices like intercropping, conservation agriculture, manuring and water harvesting, elsewhere discussed under terms like sustainable practices or conservation agriculture (Bryan et al., 2013; Ntshangase et al., 2018). Essentially, CSAT and practices contribute to the adaptation of farmers to the effects of climate change and more importantly, it helps the resource poor farmers to address climate change issues such as extreme drought, extreme precipitation, and changes in seasonal timing. In this regard, the ultimate aim of CSAT is to simultaneously increase agricultural productivity and resilience in the face of climate change, while at the same time reducing greenhouse emissions from agricultural systems (Lipper et al., 2014).

Evidence from the literature shows that the adoption of locally adapted CSAT portfolios can lead to an increase of productivity between 7 to 18% (IPCC, 2014, Challinor et al., 2014). Additionally, CSAT options typically reduce the production risk by increasing the resilience of the agricultural system (Lipper et al., 2014). As Teklewold et al. (2013) show for Ethiopia and Arslan et al. (2014) for Zambia adoption rates of CSATs among smallholders often remain low, despite the potential of CSAT to increase productivity and resilience (Branca et al., 2011). The decision of the rural farm households to adopt CSAT and practices is modeled under the assumption that most farmers are rational and risk averse, and therefore will always act to maximize expected profit. 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 traditional technologies or other previously available technologies. Therefore, CSAT and prcatices will only be appealing to households experiencing climate change effects and if the expected benefits significantly compensate for the costs. Hence, households' decision to adopt CSAT 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, Dustan, and Sadoulet, 2010).

To start with, we first specified the drivers of farm households' decision to adopt CSAT. Many studies (e.g., Nkamleu and Adesina, 2000; Hintze et al., 2003; Payne et al., 2003; Asfaw and Admassie 2004) have assessed the factors that influence the farm households' decision to adopt any new improved agricultural technology utilizing either probit or logit models. The two models are both based on the normal and logistic cumulative distribution function, respectively. The two models are quite similar, the main difference is being that the logistic distribution has slightly fatter tails. In this study, we fit the binary probit model to estimate the farm households' decisions to adopt CSAT since the response dependent variable (adoption of CSAT) is binary. The probit model is appropriate since it can resolve the problem of heteroscedasticity and satisfies the assumption of cumulative normal probability distribution (Gujarati, 2004). In addition, the probit model also includes believable error term distribution as well as realistic probabilities (Nagler, 1994).

The independent variables included in the model are age, education group membership, farm size, etc. Therefore, the probit model is specified as shown below:

$$G_i = F(M_i\gamma) + \mu_i \tag{1}$$

$$G_i = \begin{cases} 1, if \;\; adopted \;\; CSAT \;\; and \;\; practices \\ 0, otherwise \end{cases}$$

where: $\mu \sim N(0,1)$; γ = maximum likelihood; μ_i = error term; M = set of independent variables included in the model. In the case of normal distribution function, the model to estimate the probability of observing a farmer using CSAT and practices can be stated as:

$$P(G_i = 1|M) = \phi(M'\gamma) = \int_{-\infty}^{m\prime\gamma} \frac{1}{\sqrt{2\pi}} exp(-z^2/2)dz \tag{2}$$

where P is the probability that the ith farm household adopt any of the disseminated CSAT and practices, and 0 otherwise. Since the estimates of the probit model provide only direction of effects, the marginal effects are usually calculated to interpret the actual change in probability of independent variables.

$$\text{Marginal effects}=\gamma_i\ \phi(z) \quad (3)$$

where: γ_i = coefficient of the variables; $\phi(z)$ = the cumulative normal distribution value associated with the mean dependent variable from the probit estimation. To evaluate the impact of adoption of CSAT and practices on the distribution of welfare outcomes requires an estimation of the conditional linear quantile model as follows:

$$J_i^{\pi} = M_i\alpha^{\pi} + T_i\beta^{\pi} + \varphi_i \quad (4)$$

where β^{π} denotes the quantile treatment effect (QTE) of adoption of CSAT and practices T_i. J_i^{π} corresponding to the πth quantile of the distribution of the welfare outcomes. M_i is a vector of observed covariates that consist of socio-economic/demographic characteristics, etc.; α^{π} is a vector of parameters of the covariates to be estimated; φ_i is the unobserved random variable. However, since the treatment (adoption of CSAT) is non-random in the population. Implying that adoption of CSAT may be potentially endogenous to the outcome variables, using Equation (4) may lead to erroneous impact estimate.

Following Olagunju et al., 2019; Okunu and Muchapondwa, 2020; Abadie et al., 2002, and Chernozhukov and Hansen 2008 we examine the impact of adoption of CSAT on the distribution of welfare outcomes (measured in terms of per capita total households' income, and per capita total expenditure (food and non-food) employing the QTE conditional on covariates; originally developed by Abadie et al. (2002). We specify the empirical econometric model of Abadie et al. (2002) conditional IV-QTEs model as follows:

$$\beta\left(\hat{\pi}_{IV,}\widehat{\delta\pi}_{IV}\right) = argmin \sum W_i^{AAI}\,.\,\rho_{\pi}(G_i - M\beta_i - T_i\delta) \quad (5)$$

where: $= 1 - \frac{T_i(1-L_i)}{1-pr(L=1|M_i)} - \frac{(1-T_i)L_I}{pr(L=1|M_i)}$

To determine the QTE in equation (5) requires the use of an Instrumental Variable (IV) to obtain a consistent estimate of the treatment effect. However, the main concerns with respect to IV are week instruments and over identification. Moreover, if the instrument affects the farm households in various ways (heterogeneity) translating the resultant treatment effects may be problematic (Frölich & Melly, 2010). In this study, a valid IV must the strongly correlated with the farmers decision to adopt CSAT and uncorrelated with the outcome variables. Past studies on adoption and its impact on various outcomes are of the opinion that no farm household can make any new technology adoption decision without first having adequate information about the technology. Being aware of a new technology has been advocated as a valid IV for the estimation of adoption impact of new technology.

Intuitively, the farmers' awareness about the capability of CSAT to mitigate the negative effects of climate change, particularly in relation to early/extra early maturing improved varieties in places where erratic rainfall, drought and flood are big challenges can positively influence the farm households' decision to adopt CSAT. However, being aware of the existence of a new technology and its potential to increase productivity cannot impact the farm households' welfare. The farm households' welfare can be impacted only if the farm households made an active decision to adopt CSAT. Thus, awareness of CSAT has fulfilled the exclusive restriction for it to be a valid IV in this study. Where L is the IV (awareness of CSAT). Farm households with *T1* > *T0* are referred to as compliers. These are the farm households that adopted the CSAT because they are aware of CSAT.

Equation (5) is estimated using the IV-QTE command in STATA because it produces analytical standard errors that are consistent even in case of heteroscedasticity (Frölich & Melly, 2010). Given that some weights may be negative or positive, the ivqte stata command uses the local logit estimator and implements the Abadie, Angrist, and Imbens (AAI) estimator with positive weights. A substitute offered by Abadie et al. (2002) demonstrates that the following weights can be implemented as another option to W_i^{AAI}, where

$W_i^{AAI} = E\left[W_i^{AAI} | G_{i,} T_i, M_i\right]$, Which are always positive. The IV-QTE utilize the local linear regression to estimate W_i^{AAI}.

3. Variables

The Treatment and Welfare Outcome Variables

The treatment variable in this study is adoption of CSAT and practices, and it is defined as 1 if the farm household adopt any of the climate-smart agricultural technologies (early/extra early improved seed varieties, irrigation etc.) and practices (intercropping, zero tillage, soil and water management, Integrated pest Management practices etc.), and zero otherwise. The outcome variable is welfare which we proxied by income, per capita total expenditure, and food and non-food expenditure. All the outcome variables are normalized using the household size to obtain their per capita equivalent.

4. Data collection and Sampling Framework

Data were collected in the main crop producing regions of Mali. To investigate the economic impacts of adoption of CSAT, we used primary survey data. We conducted the survey on a total of 2240 farm households in different villages selected from 32 communes that cut across 4 regions of Mali. The survey was carried out from June to October 2019. A multi-stage sampling procedure was used for the selection of the targeted sample. First, four regions were purposively selected from the regions in Mali. Eight communes were selected from each of the regions, making a total of 32 communes. From each of these communes we randomly selected 5 project intervention (treated group) and 5 project non-intervention villages per commune, making a total of 10 villages per commune. Seven farm households were selected from each of the villages. Thus, we have a total of a total of 1120 project intervention households (treated group) and 1120 project non-intervention households (control group). In the communes most of the systemic issues (local policies, culture, demographic, socio-economic, and agro-ecology) are similar which could help us to control the structural differences between the intervention households (treated group) and non-intervention households (control group). All the selected households have agriculture as the main occupation production crops and some also rearing animals in addition to crop production.

A structured questionnaire was prepared and carefully administered to gather household-level primary data. Well-trained enumerators collected the data in face-to-face interviews. Data were collected on household demographic characteristics, sources of livelihoods, conditions of food security, off-farm employment, asset ownership, types and quantities of crops produced, sale of crops and output prices, household access to credit, markets and extension services, and membership of producers' associations, among many others. Moreover, the data included information on types and volume of inputs used in crop production, inputs supply arrangements, costs of inputs (hired labor, fertilizers, pesticides, and improved seeds), quality improvement practices, market outlets, and overall production and marketing challenges.

5. Results and Discussions

5.1. Variable Definition and Descriptive Statistics

Presented in Table 1 is the definition and description of the variables used for the empirical analyses. The descriptive analysis shows 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 7 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 1. 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 s(0.18)
Adoption of CSAT	1 if the farmer adopts any CSAT technology of, 0 otherwise	0.61 (0.49)
Per capita consumption expenditure	Per capita consumption expenditure (CFA)	107,739.8 (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 agricultural technologies	1 if the farmer is aware of any of the improved technologies, 0 otherwise	0.91 (0.29)
Awareness of CSAT technologies	1 if the farmer is aware of CSAT technologies and practices	0.80 (0.40)
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)

5.2. Test of Mean Differences in Welfare Outcomes

This section presents the mean differences in some selected welfare indicators, between the CSAT adopters and CSAT non-adopters. In this section, we carried out an observed evaluation of the indicators to uncover the difference in all the selected welfare indicators between the adopters and non-adopters of the CSAT, and test if the differences are statistically significant. The results as presented in Table 2 shows that the farm households that adopted the CSAT appears to have statistically significant higher values in all the selected indicators, except for the non-farm income with insignificant mean difference between adopters and non-adopters.

The simple comparison of the means of these selected welfare indicators for the adopters and non-adopters does not imply impact of adoption of CSAT technologies on the households' welfare. This is because, the presented observed differences might be due to other observed and unobserved factors that has nothing to do with adoption of CSAT technologies. In other words, the observed 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). 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 the CSAT technologies on welfare we adopted the IV-QTE.

Table 2. Test of Mean Differences in Welfare Indicators.

Variable	Total N = 2186	CSAT-Adopters N = 1332	CSAT Non-Adopters N = 854	Mean Difference	*t*-Test
Total household income (CFA)	412,929.50	452,091.70	351,847.40	100,244.40	5.32 ***
	(9244.65)	(12,297.35)	(13,607)	(18,830.41)	
Per capita total household income (CFA)	70,389.53	77,446.92	59,549.31	17,897.62	5.19 ***
	(1695.37)	(2242.526)	(2529.79)	(3448.36)	
Total income from crop production (CFA)	247,195.2	288,255.80	183,152.30	105,103.50	5.90 ***
	(8752.77)	(12,100.72)	(11,750.23)	(17,802.29)	
Total non-farm income (CFA)	131,292.40	131,363.40	1,311,081.60	181.74	0.02
	(5172.13)	(6774.14)	(7982.47)	(10,603.23)	
Total consumption expenditure (CFA)	599,729.60	645,263.00	528,710.20	116,552.90	5.09 ***
	(11,231.95)	(14,527.07)	(17,432.09)	(22,890.81)	
Per capita consumption expenditure (CFA)	108,136.80	117,921.50	93,107.50	24,813.98	5.36 ***
	(2275.65)	(2972.19)	(3469.51)	(4626.67)	
Total non-food expenditure (CFA)	658,591.20	702,929.40	589,436.00	113,493.40	2.31 **
	(24,009.00)	(26,519.97)	(45,372.88)	(49,160.17)	
Total food expenditure (CFA)	48,441.57	59,579.30	31,069.84	28,509.46	4.45 ***
	(3139.45)	(4782.06)	(2896.42)	(6407.10)	
Total Farm size (ha)	13.49	13.64	13.23	0.41	0.84
	(0.24)	(0.30)	(0.39)	(0.49)	
Total monetary value of household asset value (CFA)	1,642,478.00	1,691,304.00	156,6323.00	124,980.80	1.81 *
	(33,621.01)	(42,759.84)	(54,319.81)	(68,873.49)	
Total monetary value of productive assets (CFA)	847,241.20	919,047.80	735,243.10	18,3804.70	5.77 ***
	(15,664.93)	(20,070.50)	(24,586.09)	(31,872.43)	

Figures in parentheses are standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.3. Determinants of Adoption of Climate-Smart Agricultural Technologies

In this section, we examined the factors influencing farmers' adoption decisions for the CSAT. We used a probit model to estimate factors and the results (coefficient estimates and marginal effects) are shown in Table 3. Overall, the result confirmed that farmer's adoption decision is influenced by socioeconomic and demographic characteristics (individual and household level), social capital, institutional support to the farmers, and the farm level susceptibility to climate change.

The results show that farmers participation in climate change related training have a significant and positive relationship with the adoption of CSAT. The marginal effects suggest that participation in training increases the likelihood of adoption by 14.7%. The probable reason for this, as noted in previous studies (Stewart et al., 2015; Martey et al., 2021), is that training provides an exposure mechanism that allows farmers to have a clearer understanding of the processes and procedures of the technologies. We found that there is a negative association between farming experience and farmers adoption decisions. Studies such as Ogunniyi et al., (2017) and Sardar et al., (2020) noted that the probability of adopting improved agricultural technologies decreases with increasing farmer experience.

Household size negatively influence the adoption of CSAT. The result suggests that as household size reduces the probability of adoption of CSAT. This result is consistent with previous studies Baiyegunhi et al. (2019) and Zhang et al. (2019) that found that households with large sizes are less likely to adopt climate-smart technologies.

l. In the same vein, Mahama et al. (2020) note that large households often face a challenge of intra-household budget allocation in which food expenditure takes the large share of total household allocation leaving less to other farming expenditures such as improved inputs. The relationship between farm size and adoption of CSAT was found to be significant but negative. The result shows that the likelihood of adopting the CSAT decreases with increasing size of farms. This may be attributed to the fact that farmers may consider the cost to incur on adopting the technology on a large farm size without evaluating the economics of scale that can be beneficial due to large expanse of land.

The results of the institutional variables used in the model suggest that the adoption rate can be improved if farming households receive certain supports from relevant agencies. For instance, we found that access to information on climate change (and its impact) via mass media was positive and significantly influence the adoption of CSAT. The marginal effect shows that the probability of adoption increases by 8.2% if the farmers have access to information on climate change. This result is in line with Sardar et al. (2020) that found that farmers are more likely to adopt CSAT if there is information on the destructive impacts of climate change. Interestingly, access to credit and extension services were found to positively and significantly influence the adoption of CSAT. The result suggests that a farmer that is well endowed with productive resources such as credit facilities and has access to knowledge, skills, and awareness towards the use of CSAT through extension services are likely to adopt than farmers who do not have access to such support. Studies (Nkegbe and Shankar, 2014; Awuni et al., 2018; Mahama et al., 2020) have confirmed that access to credit facilities and extension services are very important factors that mostly form farmers' opinions and decisions for adopting an agricultural technology.

The relationship between income from agriculture and the adoption of CSAT was found to be positive and significant at 1%. Income plays an important role in the decision-making process of most farming households (Mahama et al., 2020). The result suggests that an increase in the income generated from agriculture will lead to a 9.2% increase in the likelihood of adopting CSAT. Interestingly, distance to the nearest village was found to positively influence adoption at 1% significant level. The marginal increase in the probability of adopting CSAT will be 1% in relation to the distance to the nearest village. As noted by Wang et al. (2020), closeness and connections with agricultural hubs within farmers' local localities could increase the likelihood of selling agricultural products which may increase the probability of adoption of improved agricultural technology. Social capital is an important factor that influences individual farmers' decision to adopt an improved agricultural technology. We found that membership of any organization such as a farmers' group is positive and significantly influencing the probability of adopting CSAT. The marginal effect estimate shows that farmer membership of any social group increasesthe likelihood of adopting CSAT by 11.9%. Studies (Hailu et al., 2014; Tefera et al., 2016, Wossen et al., 2017) have found that the adoption rate of improved technology can be significantly increased if the household head belongs to any association.

5.4. The Distributional Effects of CSAT Adoption on Welfare Outcomes

Table 4 presents the results of the distributional impacts of adoption of CSAT on the four welfare indicators considered in this study including per capita total consumption expenditure, per capita non-food expenditure, per capita food expenditure, and per capita total household income. The results reveal that the treatments effects of adoption of CSAT on per capita total consumption expenditure is positive and statistically significant at 1% level across all the quantiles, except for the median (Q0.50). Specifically, the impacts of CSAT, in value terms, ranges between 11,399.70 CFA Franc for households at the lowest tail of the distribution to 46,902.43 CFA Franc for those at the highest tail. These findings reflect heterogeneity in the impacts of CSAT on welfare as measured by per capita total consumption expenditure. In terms of percentage impact of the treatment effects, the findings show that the highest percentage increase of the impacts of CSAT adoption was found at the lower tails of per capita food expenditure consumption distribution.

Table 3. Estimates of determinants of adoption of CSAT.

	Probit Regression		Marginal Effects	
Variables	**Coefficient**	**Std. Error**	**dy/dx**	**Std. Error**
Number of years of residence in the village	0.003	0.002	0.001	0.001
Attend training (yes = 1)	0.404 ***	0.082	0.147 ***	0.028
Years of farming experience	−0.013 ***	0.002	−0.005 ***	0.001
Tropical Livestock Unit (TLU)	0.002	0.002	0.001	0.001
Literacy (yes = 1)	0.031	0.066	0.012	0.025
Total farm size (ha)	−0.006 *	0.003	−0.002 *	0.001
Household size	−0.013 **	0.006	−0.005 **	0.002
Access to information (television = 1)	0.216 ***	0.065	0.082 ***	0.024
Access to credit (yes = 1)	0.278 ***	0.080	0.103 ***	0.029
Age of household head (years)	0.000	0.013	0.000	0.005
Square of age	0.000	0.000	0.000	0.000
Contact with extension agents (yes = 1)	0.423 ***	0.070	0.164 ***	0.027
Household with migrant (yes = 1)	−0.047	0.063	−0.018	0.024
Main income from agriculture (yes = 1)	0.240 ***	0.064	0.092 ***	0.025
Married (polygamous = 1)	−0.066	0.069	−0.025	0.026
Distance to the nearest village (km)	0.001 *	0.001	0.001 *	0.000
Walking distance to the nearest market (min)	−0.000	0.001	−0.000	0.000
Membership of any organization(yes = 1)	0.306 ***	0.081	0.119 ***	0.032
Bank account (yes = 1)	−0.234 **	0.102	−0.091 **	0.040
Constant	−0.241	0.372		
Number of observations	2216		2216	

The adoption of CSAT significantly lead to an increase in the per capita total consumption expenditure by 53.75% and 41.70% for farming households in the 15th and the 25th quantiles, respectively, and 35.16% and 29.95% for farming households in the 75th and the 85th quantiles, respectively implying that the impacts of CSAT on per capita food consumption expenditure are higher among poorer farm households compared to farm households that are well-off. This is in line with the finding of Olagunju et al. (2020) that reported that the welfare outcomes of poorer maize farmers in rural Nigeria are more positively and significantly impacted by the adoption of improved seed varieties than well-off farmers.

The results also show that adoption of CSAT positively and significantly impact both per capita food and non-food expenditure differently across the five quantiles, ranging from 11,480.87 (Q0.15) CFA Franc to 32,515.77 (Q0.85) CFA Franc for per capita non-food expenditure, and 367.45 (Q0.15) CFA Franc to 2530.44 (Q0.85) CFA Franc for per capita food expenditure. In terms of percentage impact of CSAT, the findings show that the highest percentage increase of the effects of CSAT adoption was found at the lower tails of per capita food and non-food expenditure distributions. The adoption of CSAT significantly raised per capita non-food expenditure by 67.67% and 55.05% in the 15th and the 25th quantiles, respectively, and increased per capita food expenditure by 31.20% and 31.89% in the 15th and the 25th quantiles, respectively. The percentage impact of adoption of CSAT on per capita non-food expenditure is significantly higher than the corresponding impact on per capita food expenditure. Giving that farm households expenditure on non-food items are often larger than food items, the significant larger impact of CSAT on per capita non-food expenditure implies that adoption status will have a strong bearing on the livelihood status of rural farmers in the study area.

Finally, the results show that the impact of the adoption of CSAT is also positive and significant across the distribution of the per capita total household income. In value terms, the IV-QTE estimates show a significant and increasing pattern along the per capita total household income distribution. The largest percentage impacts of about 86.40% in the

Q.15 and 65.96% in Q0.25 were found in the lower quantiles of the per capita total household income distribution. This also suggests that adoption of CSAT impacts per capita total income of poorer households substantially, in support of the existing findings on other welfare outcomes.

Table 4. The Distributional effects of CSAT adoption on welfare.

Variable	IV-QTE Estimates				
	Q0.15	**Q0.25**	**Q0.50**	**Q0.75**	**Q0.85**
Per capita total consumption expenditure (CFA)					
Treatment effect of CSAT adoption					
	11,399.70***	13,981.77 ***	29,217.44	41,897.82 ***	46,902.43 ***
	(3395.17)	(3971.644)	(6794.67)	(10,980.83)	
% Impact of CSAT adoption $	53.75	41.70	43.73	35.16	29.95
Per Capita non-food expenditure (CFA) Treatment effect of CSAT adoption	11,480.87 ***	14,342.1 ***	22,770.61 ***	35,035.97 ***	32,515.77 **
	(3253.08)	(3724.21)	(6274.41)	(8557.16)	(15,257.77)
% Impact of CSAT adoption $	67.67	55.05	36.69	31.82	21.56
Per capita food expenditure (CFA)					
Treatment effect of CSAT adoption	367.45 **	491.15 ***	686.23 ***	1761.83 ***	2530.44 ***
	(152.35)	(166.01)	(236.54)	(462.31)	(784.94)
% Impact of CSAT adoption $	31.20	31.89	24.77	34.57	39.37
Per Capita total household income (CFA) Treatment effect of CSAT adoption	5695.735 **	10,024.48 ***	15,312.29 ***	27,182.22 ***	29,121.3 **
	(2469.954)	(3358.808)	(4637.214)	(7047.017)	(12,355.48)
% Impact of CSAT adoption $	86.40	65.96	31.94	29.04	23.82

Notes: Robust standard errors are in parentheses; **, and *** represent statistical significance at $p < 0.05$, and $p < 0.01$, respectively; $ This was estimated by dividing the treatment effect coefficient by the fitted values when the adoption binary variable is zero and other control variables are at their means for the treated (Abadie et al., 2002); All the estimated models contain the control variables and are available on request.

6. Conclusions and Policy Recommendations

This study investigates the distributional impacts of the adoption of CSAT on four welfare indicators considered including per capita total consumption expenditure, per capita non-food expenditure, and per capita food expenditure and per capita total household income. Adoption of CSAT is essential in achieving improvement in overall households' welfare. The farmers' decision to adopt any CSAT is positively and statistically influence by access to credit, contact with extension agents, participation in training, access to information through the television and being a member of any organization such as cooperative society.

The results of the test of mean difference show that the adopters of CSAT are on average better than the non-adopters in all selected indicators of welfare. The results of the IV-QTE reveal a heterogeneity in the impacts of CSAT on welfare, and the highest percentage increase of the impact of CSAT adoption was found at the lower tails of per capita food expenditure consumption distribution. This implies that the impacts of CSAT on per capita food consumption expenditure are more pronounced among poorer farm households compared to farm households that are well-off. In the same vein, the highest percentage increase of the impact of CSAT adoption was found at the lower tails of per capita food and non-food expenditure distributions and adoption of CSAT impacts per capita total income of poorer households substantially. In conclusion, the adoption of CSAT is pro-poor and we therefore recommend that climate-smart interventions should be scale-up towards the resource-poor farm households that are currently facing the adverse effects of climate change in Mali.

Institutional Review Board Statement:

Informed Consent Statement:

Data Availability Statement:

Acknowledgments: This research was funded by the Royal Norwegian Embassy, Bamako, Mali. We appreciate the farmers in the CSAT project regions (Kayes, Koulikoro, Segou and Sikasso) for the willingness to share their ideas. We are also grateful to the collaborating national partners (IER and NGOs-MaliMARK, AMEDD and Amassa Afrique vert).

References

1. Abadie, A.; Angrist, J.; Imbens, G. Instrumental variables estimates of the effect of subsidized training on the quantiles of trainee earnings. *Econometrica* **2002**, *70*, 91–117.
2. Abate, G.T.; Rashid, S.; Borzaga, C.; Getnet, K. Rural finance and agricultural technology adoption in Ethiopia: Does the institutional design of lending organizations matter? *World Dev.* **2016**, *84*, 235–253.
3. Abdulai, A.; Huffman, W. The adoption and impact of soil and water conservation technology: An Endogenous switching regression application. *Land Econ.* **2014**, *90*, 26–43.
4. Asfaw, A.; Admassie, A. The role of education on the adoption of chemical fertiliser under different socioeconomic environments in Ethiopia. *Agric. Econ.* **2004**, *30*, 215–28.
5. Atella, V.; Pace, N.; Vuri, D. Are employers discriminating with respect to weight? European evidence using quantile regression. *Econ. Hum. Biol.* **2008**, *6*, 305–329.
6. Bishop, J.A.; Luo, F.; Wang, F. Economic transition, gender bias, and the distribution of earnings in China. *Econ. Transit.* **2005**, *13*, 239–259.
7. Chernozhukov, V.; Hansen, C. An IV model of quantile treatment effects. *Econometrica* **2005**, *73*, 245–261.
8. Chernozhukov, V.; Hansen, C. The effects of 401 (k) participation on the wealth distribution: An instrumental quantile regression analysis. *Rev. Econ. Stat.* **2004**, *86*, 735–751.
9. Chernozhukov, V.; Hansen, C.B. *Massachusetts Institute of Technology*; Department of Economics: 2006; Instrumental Variable Quantile Regression; Massachusetts Institute of Technology, Department of Economics: 2006.
10. Chernozhukov, V.; Hansen, C. Instrumental variable quantile regression: A robust inference approach. *J. Econom.* **2008**, *142*, 379–398.
11. Chen, L.A.; Portnoy, S. Two-stage regression quantiles and two-stage trimmed least squares estimators for structural equation models. *Commun. Stat.-Theory Methods* **1996**, *25*, 1005–1032.
12. De Janvry, A.; ; Sadoulet, E. Agricultural growth and poverty reduction: Additional evidence. *World Bank Res. Obs.* **2010**, *25*, 1–20.
13. Di Falco, S.; Chavas, J.P. On crop biodiversity, risk exposure and food security In the highlands of Ethiopia. *Am. J. Agric. Econ.* **2009**, *91*, 599–611.
14. Di Falco, S.; Veronesi, M. How can African agriculture adapt to climate change? A counterfactual analysis from Ethiopia. *Land Econ.* **2013**, *89*, 743–766.
15. Evenson, R.E.; ; D Gollin. Assessing the Impact of the Green Revolution, 1960 to 2000. *Science* **2003**, *300*, 758–62.
16. Falaris, E.M. A quantile regression analysis of wages in Panama. *Rev. Dev. Econ.* **2008**, *12*, 498–514.
17. FAO; IFAD; UNICEF; WFP; WHO. *The State of Food Security and Nutrition in the World 2019. Safeguarding Against Economic Slowdowns and Downturns*; FAO: Rome, Italy, 2019.
18. Food and Agriculture Organization of the United Nations. *Climate-Smart Agriculture Source Book*; Food and Agriculture Organization: Rome, Italy, 2013.
19. Frölich, M.; Melly, B. Estimation of quantile treatment effects with Stata. *Stata J.* **2010**, *10*, 423.
20. Gollin, D. Agricultural Productivity and Economic Growth. *Handb. Agric. Econ.* **2010**, *4*.
21. Gujarati, D. *Basic Econometrics*, 4th ed.; McGraw-Hill: New York, NY, USA, 2004; p. 1001
22. Hintze, L.H.; M. Renkow; and G. Sain. Variety characteristics and maize adoption in Honduras. *Agric. Econ.* **2003**, *29*, 307–17.
23. IPCC. *Climate Change 2014: Mitigation of Climate Change: Working Group III Contribution to the IPCC Fifth Assessment Report, Working Group III Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*; IPCC: Geneva, Switzerland, 2014. https://doi.org/10.1017/CBO9781107415416.
24. Kato, E.; Ringler, C.; Yesuf, M.; Bryan, E. Soil and water conservation technologies: A buffer against production risk in the face of climate change? Insights from the Nile basin in Ethiopia. *Agric. Econ.* **2011**, *42*, 593–604.
25. Khatri-Chhetri, A.; Pant, A.; Aggarwal, P.K.; Vasireddy, V.V.; Yadav, A. Stakeholders prioritization of climate-smart agriculture interventions: Evaluation of a framework. *Agric. Syst.* **2019**, *174*, 23–31.
26. Koenker, R.; Bassett, G., Jr. Regression quantiles. *Econom. J. Econom. Soc.* **1978**, *46*, 33–50.
27. Koenker, R.; Hallock, K.; Quantile regression: An introduction. *J. Econ. Perspect.* **2001**, *15*, 43–56.
28. Lipper, L.; Thornton, P.; Campbell, B.M.; Baedeker, T.; Braimoh, A.; Bwalya, M.; Caron, P.; Cattaneo, A.; Garrity, D.; Henry, K.; et al. Climate-smart agriculture for food security. *Nat. Clim. Chang.* **2014**, *4*, 1068–1072. https://doi.org/10.1038/nclimate2437.
29. Lipper, L.; Thornton, P.; Campbell, B.M.; Baedeker, T.; Braimoh, A.; Bwalya, M.; Caron, P.; Cattaneo, A.; Garrity, D.; Henry, K.; et al. Climate-smart agriculture for food security. *Nat. Clim. Chang.* **2014**, *4*, 1068–1072.
30. Martey, E.; Etwire, P.M.; Mockshell, J. Climate-smart cowpea adoption and welfare effects of comprehensive agricultural training programs. *Technol. Soc.* **2021**, *64*, 101468.

31. Melly, B. *Public and Private Sector Wage Distributions Controlling for Endogenous Sector Choice*; Swiss Institute for International Economics and Applied Economic Research: Mimeo, Singapore, 2006.
32. Mendelsohn, R.O.; Dinar, A. *Climate Change and Agriculture: An Economic Analysis of Global Impacts. Adaptation and Distributional Effects*; Edward Elgar Publishing: Cheltenham, UK, 2009.
33. Nagler, J. *Interpreting Probit Analysis*; New York University: New York, NY, USA, 1994.
34. Ng'ombe, J.N.; Kalinda, T.H.; Tembo, G. Does adoption of conservation farming practices result in increased crop revenue? Evidence from Zambia. *Agrekon* **2017**, *56*, 205–221.
35. Nkamleu, Guy Blaise and Akinwumi A. Adesina. Determinants of chemical input use in peri-urban lowland systems: Bivariate probit analysis in Cameroon. *Agric. Syst.* **2000**, *63*, 111–21.
36. Nkala, P.; Mango, N.; Corbeels, M.; Veldwisch, G.J.; Huising, J. The conundrum of conservation agriculture and livelihoods in Southern Africa. *Afr. J. Agric. Res.* **2011**, *6*, 5520–5528.
37. Nkegbe, P.K.; Shankar, B. Adoption intensity of soil and water conservation practices by smallholders: Evidence from Northern Ghana. *Bio-Based Appl. Econ. J.* **2014**, *3*, 159–174.
38. Ogunniyi, A.; Oluseyi, O.K.; Adeyemi, O.; Kabir, S.K.; Philips, F. Scaling-up agricultural innovation for inclusive livelihood and productivity outcomes in sub-Saharan Africa: The case of Nigeria. *Afr. Dev. Rev.* **2017**, *29*, 121–134.
39. Olagunju, K.O.; Ogunniyi, A.I.; Awotide, B.A.; Adenuga, A.H.; Ashagidigbi, W.M. Evaluating the distributional impacts of drought-tolerant maize varieties on productivity and welfare outcomes: An instrumental variable quantile treatment effects approach. *Clim. Dev.* **2020**, *12*, 865–875.
40. Payne, J.; Fernandez-Cornejo, J.; Daberkow, S. Factors Affecting the Likelihood of Corn Rootworm Bt Seed Adoption. *AgBioForum* **2003**, *6*, 79–86.
41. Ravallion, M.; Datt, G. How important to India's poor is the sectoral composition of growth in India. *World Bank Econ. Rev.* **1996**, *10*, 1–25.
42. Sabiha, N.E.; Salim, R.; Rahman, S. Eco-efficiency of high-yielding variety rice cultivation after accounting for on-farm environmental damage as an undesirable output: An empirical analysis from Bangladesh. *Aust. J. Agric. Resour. Econ.* **2017**, *61*, 247–264.
43. Seo, S.; Mendelsohn, R.; Dinar, A.; Hassan, R.; Kurukulasuriya, P. A Ricardian analysis of the distribution of climate change impacts on agriculture across agro-ecological zones in Africa. *Environ. Resour. Econ.* **2009**, *43*, 313–332.
44. Sardar, A.; Kiani, A.K.; Kuslu, Y. Does adoption of climate-smart agriculture (CSA) practices improve farmers' crop income? Assessing the determinants and its impacts in Punjab province, Pakistan. *Environ. Dev. Sustain.* **2020**, 1–22.
45. Solis, D.; Bravo-Ureta, B.E.; Quiroga, R.E. Soil conservation and technical efficiency among hillside farmers in Central America: A switching regression model. *Aust. J. Agric. Resour. Econ.* **2007**, *51*, 491–510.
46. Tefera, T.; Tesfay, G.; Elias, E.; Diro, M.A.; Koomen, I. *Drivers for Adoption of Agricultural Technologies and Practices in Ethiopia*; CASCAPE Project Report No. NS_ DfA_2016_1, Addis Ababa/Wageninge; 2016.
47. Teklewold, H.; Kassie, M.; & Shiferaw, B.A. *On the Joint Estimation of Multiple Adoption Decisions: The Case of Sustainable Agricultural Technologies and Practices in ETHIOPIA* (No. 126885); International Association of Agricultural Economists: Toronto, ON, Canada, 2012.
48. Teklewold, H.; Kassie, M.; Shiferaw, B.; Köhlina, G. Cropping system diversification, conservation tillage and modern seed adoption in Ethiopia: Impacts on household income, agrochemical use and demand for labor. *Ecol. Econ.* **2013**, *93*, 85–93.
49. United Nations. *World Population Prospects 2019*; Department of Economic and Social Affairs Population Dynamics: USA, 2019.
50. Veettil, P.C.; Krishna, V.V.; Qaim, M. Ecosystem impacts of pesticide reductions through Bt cotton adoption. *Aust. J. Agric. Resour. Econ.* **2017**, *61*, 115–134.
51. Wang, G.; Lu, Q.; Capareda, S.C. Social network and extension service in farmers' agricultural technology adoption efficiency. *PLoS ONE* **2020**, *15*, e0235927.
52. Wani, S.P.; Sreedevi, T.K.; Rockstrom, J.; Ramakrishna, Y.S. Rainfed agriculture—Past trends future prospects. In *Rainfed Agriculture. Unlocking the Potential*; Wani, S.P., Rockstrom, J., Oweis, T., Eds.; CAB International: Wallingford, UK, 2009.
53. Wehby, G.L.; Murray, J.C.; Castilla, E.E.; Lopez-Camelo, J.S.; Ohsfeldt, R.L. Quantile effects of prenatal care utilization on birth weight in Argentina. *Health Econ.* **2009**, *18*, 1307.
54. World Bank. *Poverty and Shared Prosperity: Taking on Inequality*; World Bank: Washington, DC, USA, 2016;. https://doi.org/10.1596/978-1-4648-0958-3.
55. World Bank. *Republic of Niger: Impacts of Sustainable Land Management Programs on Land Management and Poverty in Niger*; Report No. 48230-NE; World Bank: Washington, DC, USA, 2009.
56. Wossen, T.; Abdoulaye, T.; Alene, A.; Haile, M.G.; Feleke, S.; Olanrewaju, A.; Manyong, V. Impacts of extension access and cooperative membership on technology adoption and household welfare. *J. Rural Stud.* **2017**, *54*, 223–233.
57. Yasar, M.; Nelson, C.H.; Rejesus, R. Productivity and exporting status of manufacturing firms: Evidence from quantile regressions. *Rev. World Econ.* **2006**, *142*, 675–694.
58. Zougmore, R.; Jalloh, A.; Tioro, A. Climate-smart soil water and nutrient management Options in semi-arid West Africa: A review of evidence and analysis of stone bunds and Zaı techniques. *Agric. Food Secur.* **2014**, *3*, 1–8.