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ICTs Use, Agroforestry Technologies' Adoption and Crop Farmers' Welfare: An Empirical Evidence from Southwest, Nigeria

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Abstract

There is a glaring shortage of studies on the impact of ICTs use on the adoption of agroforestry technologies and combined effects of ICTs use and agroforestry technologies' adoption on farmers' welfare. To fill the information gap, this study examined the impact of ICTs use on agroforestry technologies' adoption and their heterogenous impacts on crop farmers' welfare in Southwest, Nigeria. Endogenous-treatment poisson regression (ETPR) model and unconditional quantile regression (UQR) model were used to analyse the data collected from 488 respondents. The results indicated that the use of ICTs improved the adoption of agroforestry technologies which facilitate friendly environment. Also, ICTs use and agroforestry technologies' adoption statistically and heterogeneously influenced farm revenue and household food insecurity access scale (HFIAS). Precisely, ICTs use had the highest influence on farm revenue at the lowest quantile, while agroforestry technologies' adoption had the highest effect on household food insecurity access scale (HFIAS) at the lowest quantile. Therefore, policies that promote crop farmers' access to ICTs should be the priority of policy makers who are interested in the welfare of crop farmers and increased farmers' level of agroforestry technologies' adoption.

Keywords

ICTs, agroforestry, HFIAS, revenue, RIF, UQR, ETPR, IRR.

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Introduction

It is a known fact that Nigeria's climate has been changing as shown by temperature increase; inconsistent rainfall pattern; increase in flooding and sea-level; desertification and drought; land degradation and so on, which have been leading to loss of biodiversity and affecting fresh water resources (Elisha et al., 2017). The contributing factors to the land degradation include population explosion, unsustainable agricultural practices, mining, infrastructural development and energy. Land degradation has resulted to unemployment, flood, erosion, food insecurity, desertification and conflict over resources. Therefore, adoption of sustainable agricultural technologies that improve and sustain agricultural production must be promoted. Agroforestry is one of such agricultural technologies, which is a land-use measure that addresses the issue of climate change and provides other ecological, pecuniary and social gains (Waldron et al., 2017).

According to Minang et al. (2014), one of the means of evading deforestation, reducing CO_2 emissions and lessening climate change is agroforestry. In developing countries like Nigeria, deforestation is a critical issue primarily due to subsistence and commercial agriculture being practiced (Weatherly-Singh and Gupta, 2015). Campaign in favour of agroforestry is important because of its potential for carbon sinking, control of soil erosion, improved nutrients and water cycling, socio-economic gains and higher agricultural yield (Fagerholm et al., 2016; Wilson et al., 2016). Agricultural production, productivity and farm income can be increased using agricultural technologies (Tambo and Mockshell 2018; Rola-Rubzen et al., 2019). According to Mekonnen (2017), boosting agricultural yield enhances the welfare of farmers by raising food availability and decreasing agricultural outputs' prices.

According to Jack and Tobias (2017), over the years, information and communications technologies (ICTs) have been seen as important part of farmers' lives in Africa. Information and communication technologies (ICTs) (for instance, mobile phones) have gained the attention of donor agencies as they are being used as tools in supporting transfer of knowledge and encouraging acceptance and spread of innovations (Aker et al., 2016; Westermann et al., 2018). Information and communications technologies (ICTs) have the capacity to assist in improving agricultural technologies adoption. Sharing information through ICTs can enlighten crop growers about new technologies and state of market, such as prices, which helps to resolve on where and when to trade their agricultural commodities (Aker, 2010). Therefore, ICTs present a means through which maintainable economic and social development are supported in rural African countries. ICTs allow farmers to have access to a more comprehensive set of information and technologies capable of increasing productivity, improving market access, and contributing to household revenues and food security (Voss et al., 2021).

The Impact of ICTs use on welfare of farmers (Zhu et al. 2020), agricultural technologies' adoption on welfare of farmers (Mendola, 2007; Mekonnen, 2017), internet use on adoption of agricultural technologies (Zheng et al. 2022; Zheng et al. 2023) have been well documented in the literature. This is not so in the case of impact of agroforestry technologies' adoption on farmers' welfare which is very scarce in the literature. Also, there is a glaring shortage of studies on the impact of ICTs use on the adoption of agroforestry technologies in the literature. As far as I know, this is the first study that estimates the joint effects of ICTs use and agroforestry technologies' adoption on farmers' welfare. It is therefore, imperative to carry out this study that answers the following research questions; what is the impact of ICTs use on agroforestry technologies' adoption among crop farmers? and what is the heterogenous impact of ICTs use and agroforestry technologies' adoption on the respondents' welfare? The welfare indicator used in this study are farm revenue and household food insecurity access scale (HFIAS).

This research contributes to the existing body of knowledge in the literature in four ways. To start with, many studies are around the impact of farming technologies on wellbeing without specifically considering the impact of agroforestry technologies adoption on crop farmers' welfare. Therefore, this study fills the gap in the literature by examining the impact of agroforestry technologies' adoption on the welfare of crop farmers. Furthermore, there is little or no information on studies that investigated the impact of ICTs use on agroforestry technologies' adoption in the literature, which this study examined. Moreover, endogenous-treatment poisson regression (ETPR) model is used for the purpose of correcting selection bias related to voluntary ICTs use through the consideration of both observed and unobserved heterogeneities. This is lacking in the literature because the only study that considered this issue was on internet use and sustainable agricultural practices in China. More so, the heterogeneous effects of ICTs use and agroforestry technologies' adoption on farmers' welfare is examined by modelling the two together using unconditional quantile regression (UQR) model. Studies in the literature either investigated the effect of ICT use on welfare (Ma et al., 2018; Zhu et al., 2022) or impact of agricultural technologies adoption on farmers' welfare (Adams and Jumpah, 2021; Kopalo et al., 2021) without modelling the two together. The effects of ICT use and agroforestry technologies' adoption on welfare should be jointly modelled because of likely interdependence between them. Evidence from this study will assist policymakers as well as other stakeholders to formulate policies that engender sustainable agricultural development in Nigeria. It equally gives empirical evidence that can be used to encourage farmers to embrace agroforestry technologies for the purpose of having increase in productivity and skill intensive activities on the farm, which lead to improved welfare.

Materials and methods

Data used in this study were gotten from the survey of crop farming families which took place in January 2022. The respondents used for the study were selected using a multistage sampling procedure. To start with, random sampling technique was used to pick two States out of six States in Southwest, Nigeria. Furthermore, random sampling technique was used to pick five Local Government Areas (LGAs) from the respective States chosen. Moreover, five communities were chosen from each of the chosen LGAs. More so, ten arable crop farmers were randomly picked from each of the chosen communities. The selection was made possible through information gotten from Agricultural Development Project (ADP) Offices in the two States. Eventually, the process resulted in the collection of data from 282 ICTs users and 218 non-users totaling 500 respondents. As it is typical of data collection in Nigeria, few of the respondents were not cooperative which made them to supply data that are not usable. As a result of this, data from 488 respondents were used for the analysis, while data from the remaining 12 respondents were removed from the analysis. A well-organized questionnaire which was used to collect the data covered socio-economic characteristics, agroforestry technologies adopted, farm revenue, use of information and communication technologies (ICTs), credit constraints, land ownership, food security related questions and so on. Descriptive statistics, endogenous-treatment poisson regression (ETPR) model and unconditional quantile regression (UQR) model were used to analyse the data. Household food insecurity access scale (HFIAS) was used to measure food security status of the respondents.

Coates et al. (2007); Maxwell et al. (2014) stated that HFIAS is a measure of the psychological and behavioural dimensions of food insecurity with respect to food access. The measurement is from zero to twenty-seven, with zero suggesting a family with no record of food insecurity. The highest value of twenty-seven signifies the maximum level of food insecurity, with high occurrence of eating less food and skipping meals because of inadequate food access (Coates et al., 2007). Agroforestry technologies' adoption was measured as a count variable in this study. Considering the prevalent agroforestry technologies in the study area, farmers were asked to identify the technologies they adopted in the last cropping season. The final list of agroforestry technologies used are home gardens, alley cropping, windbreaks, improved fallow, fuel wood production, silvopastoral system and apiculture with trees. Once a farmer indicated that he or she adopted any of the strategy, one (1) is assigned and zero otherwise.

Estimation strategies

Selection of model and issue of selection bias

The decision to use ICTs is not random but voluntary by farming households (Leng et al., 2020). There may be steadily diverse characteristics between arable crop farmers who used ICTs (that is, treated group) and those who did not use ICTs (that is, control group). Estimation of impact of ICTs use on agroforestry technologies' adoption (a count variable that measures the number of technologies adopted) through Poisson regression approach would give estimates that are biased when there is an existence of self-selection issue. Studies in the literature have estimated the effects of technology acceptance or intervention programme using propensity score matching (PSM) method (e.g Hou et al., 2019: Ma and Wang, 2020) and inverse-probability weighted regression adjusted (IPWRA) estimator (e.g Adolwa et al., 2019: Ma and Wang, 2020). The two approaches (that is, PSM and IPWRA) alleviate the issue of selection bias based on observed heterogeneities without addressing unobserved factors (such as farmers' innate abilities and motivations) that affect farmers' decision to use ICTs and agroforestry technologies concurrently. Normative assumptions underlie this study since there are some unobservable factors that can influence outcome variables of the two groups (users and non-users). Therefore, estimates from IPWRA and PSM would be unfair. It is against this background that this study employed an endogenous-treatment Poisson regression (ETPR) model to estimate the impact of ICTs use on agroforestry technologies' adoption (a poisson distributed count) as used by Ma and Wang (2020). The issue of selection bias emanating from both noticeable and unnoticeable factors is addressed by ETPR model, which can also estimate the treatment effects of ICTs use on agroforestry technologies' adoption.

Selection of ETPR model

The estimation using this model has a two-stage approach with farming household's decision to use ICTs being modelled in stage one. The decision of crop farming households to use of ICTs is modelled in a framework that uses random utility as done by Ma et al. (2020). Let D_i^* represent the difference in utility between the use of ICTs (I_{iU}) and utility from non-use of ICTs (I_{iN}) to the extent that a crop farming household will decide to use ICTs when $D_i^* = I_{iU} - I_{iN} > 0$. It is worthy of note that the utilities for the two groups cannot be observed. Using alternative way, the two utilities can be mathematically stated as a function of components that are observable in a latent variable model as:

$$D_i^* = \alpha_i K_i + \mu_i \; with \; D_i = \begin{cases} 1 & if \;\; D_i^* > 0 \\ 0 & otherwise \end{cases} \qquad (1)$$

where D_i^* stands for a latent variable which is for the ICTs use probability. The latent variable is gotten by the observed variable D_i which shows the actual ICTs use status of the respondents (that is, $D_i = 1$ if crop farming household i uses ICTs, while $D_i = 0$ otherwise); K_i represents crop farming family and farm-related characteristics (for example, age, farm size and education); α_i stands for the parameters to be estimated; and μ_i represents a random error term.

According to Westermann et al. (2018), information and communication technologies (ICTs) are being used as apparatuses in supporting transfer of knowledge, adoption and spread of innovations. It is on this premise that the impact of ICTs use on agroforestry technologies' adoption is identified in the stage two of the ETPR model estimation. Let us assume that agroforestry technologies' adoption is a linear function of ICTs use being a dichotomous variable and other independent factors, M_i, the agroforestry technologies' adoption function is then mathematically shown as:

$$A_i = \delta_i D_i + \tau_i M_\mathrm{i} + \epsilon_i \quad (2)$$

where A_i denotes variable for the adoption of agroforestry technologies (number of agroforestry technologies adopted); D_i is the ICTs use; δ_i and τ_i are parameters to be estimated; ϵ_i denotes an error term. The parameter δ_i is used to quantify the impact of ICTs use on the level of agro-forestry technologies' adoption. As a minimum, one variable known as an instrument should be included in K_i in Equation 1 but not in M_i in Equation 2. This is done for model identification purpose. The instrumental variable is only effective if it influences crop farmers' decision to use ICTs but does not directly affect farmers' decision to adopt agroforestry technologies. In this study, the instrument used is a variable that describes whether crop farming household's neighbour uses ICTs to buy goods online or not. Peer influence can make a crop farming household to decide to use ICTs because his or her neighbor uses ICTs but does not influence the farming household's agroforestry technologies' adoption decision directly. Appendix 1 shows the Pearson correlation test results for the soundness of the instrument used.

It is to be noted that only partial information about relationship between ICTs use and agroforestry technologies' adoption is provided by the coefficients of the variables in the ETPR model. It is against this background that average treatment effects (ATE) and average treatment effects on the treated (ATT) were calculated for the purpose of having more understanding about the impact of ICTs use on agroforestry technologies' adoption as follows:

$$ATE = E(V_{1i} - V_{0i}) = E\{E(V_{1i} - V_{0i} \mid K_i)\} \quad (3)$$

$$ATT = E(V_{1i} - V_{0i} \mid D_i = 1) = E\{E(V_{1i} - V_{0i} \mid K_i, D_i = 1) \mid D_i = 1\} \quad (4)$$

Both ICTs users and non-users were included in the sample used to estimate ATE, while data from ICTs users (treated group) only were used to estimate ATT in a counterfactual context.

Selection of UQR model

Previous studies in the literature separately analysed the impact of ICTs use on welfare (Ma et al., 2018; Zhu et al., 2022) or impact of agricultural technologies' adoption on farmers' welfare (Adams and Jumpah, 2021; Kopalo et al., 2021) without modelling the two together. The effects of ICT use and agroforestry technologies' adoption on welfare should be jointly modelled because of likely interdependence between them. Therefore, this study did not only capture the interaction between ICTs use and agroforestry technologies' adoption on crop farmers' welfare but also checked how ICTs use and agroforestry technologies' adoption affect distributions of farmers' welfare. This is the reason for considering quantile regression model analysis. According to Mishra et al. (2015) and Ma et al. (2020), conditional quantile regression model estimation largely depends on the covariates that are employed and freely altering the control variables is not possible without redefining the quantiles. Hence, an unconditional quantile regression (UQR) model is estimated to capture the heterogenous effects of ICTs use and agroforestry technologies adoption on farmers' welfare (farm revenue and HFIAS).

A UQR model can be estimated like a simple OLS regression on a regressand that is transformed using the recentered influence function (RIF) (Firpo et al., 2009). The equation to be estimated is given as follows:

$$IF(V_i;Q_\sigma,L_V) = \beta_i D_i' + \rho_i A^{i'} + \omega_i M_i + \varphi_i \quad (5)$$

where V_i denotes an outcome variable (that is, farm revenue or HFIAS); Q_σ refers to the σ-th quantile of the cumulative distribution (L_V) of the outcome; D_i' is the predicted ICTs use and A_i' is the predicted agroforestry technologies' adoption variable. The reason for the use of predicted variables instead of the original variables is to adequately address the endogeneity issue of ICTs use and agroforestry technologies' adoption variables (Chang and Mishra, 2012). The explanatory variables are represented by M_i; β_i, ρ_i and ω_i are the parameters to be estimated; and φ_i represents error term which captures unobserved heterogeneities. Specifically, the RIF in Equation 5 is expressed as follows:

$$\hat{RIF}(V_i; Q_\sigma, L_V) = Q_\sigma + \frac{\sigma - I(V_i \leq Q_\sigma)}{l_V(Q_\sigma)} \quad (6)$$

where l_V is the probability distribution function of variable V_i, while $I(V_i \leq Q_\sigma)$ shows whether the outcome variable (farm revenue or HFIAS) is below Q_σ and it is captured as a dummy variable.

Results and discussion

Description of variables used in the model

Table 1 shows the description and descriptive statistics of the variable used in the study where about 55.0% of the sampled crop farmers used ICTs. This indicates that fairly more than half of the sample used ICTs. The average number of agroforestry technologies adopted by the respondents is 0.79, indicating low adoption rate of these technologies. Adesina and Chianu (2002) reported that some farmers have not been adopting agroforestry technologies in spite of the farmers' awareness and associated gains. The little rate of adoption of agroforestry technologies have been linked to some factors in the literature (Owombo and Idumah, 2017). On the average, the log of farm revenue and household food insecurity access scale of the sampled crop farming households are 12.77 and 15.66, respectively. The mean age of a household heads is 47 years and 75% of the respondents are males. Also, the average number of years spent in school by the respondents is 10 years. On the average, the household size and farm size of the respondents are 7 and 2.27 hectares, respectively.

Differences in the variables between users and non-users of ICTs

The differences in the mean values of the selected variables between ICTs users and non-users are presented in Table 2. It is indicated that there are momentous differences between ICTs users and non-users in some of the variables. For instance, ICTs users adopted more agroforestry technologies and recorded higher revenue than non-users of ICTs with the difference of 0.23 and 2.34 respectively. The household food insecurity access scale for ICTs users is less than the one recorded by the non-users, indicating that ICTs users were more food secure than non-users. According to Aker (2010), ICTs have the capacity to assist in improving agricultural technologies adoption. Also, these results just confirmed the assertion of Voss et al. (2021) which states that ICTs allow farmers to have access to a more comprehensive set of information and technologies capable of increasing household incomes and food security. It is indicated in Table 2 that ICTs users are likely

Variables	Description	Mean	Standard Deviation
ICTs use	1 if household adopted ICT, 0 otherwise	0.55	0.50
Agroforestry technologies' adoption	The number of agroforestry technologies adopted by a household	0.79	0.63
Log of revenue	Log of farm revenue	12.77	1.14
HFIAS	Household food insecurity access scale	15.66	5.32
Sex	1 if male, 0 otherwise	0.75	0.44
Age	Age of the respondents in years	47.23	8.71
Years of education	Number of years spent in school	10.14	4.88
Household size	Number of people living in a household	7.39	2.29
Farm size	Area of land cultivated in hectares	2.27	1.63
Farming experience	Number of years spent in farming	11.66	9.03
Hours spent on farm	Number of hours spent on farm per day	5.81	2.59
Extension visits	Number of extension visits per month	0.85	1.34
Cooperative membership	1 if a member of cooperative society, 0 otherwise	0.47	0.50
Credit constraints	1 if non-credit constrained, 0 otherwise	0.50	0.40
Non-farm income	1 if farmer has non-farm income, 0 otherwise	0.52	0.50
Land right	1 if farmer has use and transfer right, 0 use only right	0.44	0.50
Neighbours using ICT	1 if neighbour uses ICT, 0 otherwise	0.40	0.49

Source: Author's estimations based on data from survey 2022

Table 1: Description and descriptive statistics of the variables used in the study.

Variables	ICTs Users	ICTs Non-users	Mean Difference
Agroforestry technologies' adoption	0.80	0.57	0.23*
Log of revenue	12.68	12.42	0.26*
HFIAS	14.66	17.00	-5.34***
Sex	0.71	0.79	-0.08
Age	45.32	48.65	-3.33***
Years of education	10.32	9.89	0.43
Household size	7.29	7.52	-0.23
Farm size	2.51	1.96	0.55***
Farming experience	14.58	7.75	6.83***
Hours spent on farm	5.61	6.09	-0.48*
Extension visits	0.76	0.97	-0.21
Cooperative membership	0.50	0.43	0.08
Credit constraints	0.38	0.67	-0.29***
Non-farm income	0.62	0.38	0.24***
Land right	0.46	0.41	0.05
Neighbours using ICT	0.47	0.31	0.16***
Observations	270	218	

Note: ***P < 0.01, **P < 0.05, *P < 0.1

Source: Author's estimations based on data from survey 2022

Table 2: The differences in the mean values of the selected variables between ICTs users and non-users

to be non-credit constrained, younger, have larger farm size and more experienced than their non-users' counterparts in the study area. Higher revenue and farming experience are recorded by the ICTs users than non-users. Having these fantastic results in favour of ICTs users cannot be said to be satisfactory since some confounding factors such as age, farm size, household size and farmers' innate abilities have not been accounted for. These confounding factors also influence crop farmers' resolve to use ICTs. Hence, the reason for more rigorous analysis of the impact of ICTs use on agroforestry technologies adoption, farm revenue and food security using robust econometric methods.

Factors influencing ICTs use

The impact of ICTs use on adoption of agroforestry technologies is presented in Table 3. The significant value of the correlation between the treatment-assignment error and the outcome error is -0.552. This signposts the existence of negative selection bias which means that there are some unobservable factors that have direct influence on the probability of using ICTs but inversely related to the number of agroforestry technologies adopted by the crop farmers. Therefore, it is sufficed to state that ETPR model is more suitable because PSM method and Poisson regression model would have underestimated the impact of ICTs use on the adoption of agroforestry technologies.

Table 3 shows that years of education, farm size, cooperative membership, credit constraints, non-farm income and neighbours using ICTs were the significant determinants of ICTs use among the sampled crop farmers in the study area. The coefficient of years of education is positive and statistically significant, indicating that higher number of years of education increased the likelihood of using ICTs. This is in congruence with Aldosari, et al. (2019); Salam and Khan (2020) who reported a direct association between education and the decision to use ICTs. The coefficient of farm size has a direct and significant association with decision to use ICTs, while non-farm income has an inverse relationship with decision to use ICTs. This indicates that rise in farm size increased the probability of using ICTs, while increase in income from non-farm source(s) would reduce the probability of using ICTs. The inverse relationship between non-farm income and probability of using ICTs is not expected because income generation from other sources of income outside farming activities should help in the procurement of ICT tools. This relationship between farm size and likelihood of using ICTs confirmed the findings of Chhachhar and Memon (2019); Leng et al. (2020) who reported that rise

Variables	ICTs use	Agroforestry technologies adoption	Agroforestry technologies adoption
ICT use		0.556**(2.18)	1.744**
Sex	0.168 (1.64)	0.078 (0.54)	1.081
Age	-0.012 (0.45)	-0.004 (0.54)	0.996
Years of education	0.012*** (5.12)	0.020* (1.86)	1.020*
Household size	0.036 (1.45)	0.063*** (2.91)	1.065***
Farm size	0.082*** (4.21)	-0.003 (0.06)	0.997
Farming experience	-0.097 (1.21)	0.016* (1.85)	1.016*
Hours spent on farm	-0.079 (1.72)	0.023 (1.02)	1.023
Extension visits	0.060 (0.23)	-0.014 (0.46)	0.986
Cooperative membership	0.118*** (6.31)	0.215* (1.88)	1.240*
Credit constraints	0.684*** (3.47)	0.143** (2.00)	1.154**
Non-farm income	-0.577** (1.97)	0.191 (1.44)	1.210
Land right	0.163 (0.89)	0.311*** (2.41)	1.365***
Neighbours using ICTs	0.585*** (3.91)		
Constant	0.834 (0.71)	0.556 (2.18)	1.744
$\rho_{\mu\varepsilon}$	-0.552 (7.23)		
Wald Test (rho = 0)	Chi^2 (1) = 41.41, Prob > Chi^2 = 0.0000		
Observation	488		

Note: Figures in bracket represent t-value. Standard errors in parentheses; ***P < 0.01, **P < 0.05, *P < 0.1.
Source: Author's estimations based on data from survey 2022

Table 3: Impact of ICT use on adoption of agroforestry technologies.

in farm size would raise the likelihood of using ICTs. The results further reveal that being a member of cooperative society and non-credit constrained increased the likelihood of using ICTs. This finding is like the report of Wawire et al. (2017) where membership of farmers' organization was reported to have increased the farmers' chance of using ICTs. However, this result contradicts the findings of Mdoda and Mdiya (2022) where it was stated that having access to credit reduced the probability of using ICTs. Lastly, the coefficient of neighbours using ICTs has a direct and significant nexus with the likelihood of using ICTs as expected because the variable is used as an instrumental variable which should be significant. This implies that the use of ICTs by crop farming household's neighbour made the farming household to decide to use ICTs.

Factors determining adoption of agroforestry technologies

The factors that influenced the number of agroforestry technologies adopted are presented in column three of Table 3. For better understanding and ease of interpretation, the incidence rate ratios (IRRs) is calculated and presented in column four of Table 3. This is necessary since the interpretation of the coefficients of the variables from count model regression is not always straightforward. Zhang et al. (2019) explained that IRRs are gotten by taking the exponential of the coefficients of the count regression model (IRR = exp (regression coefficient)).

The variable ICTs use has an IRR that is positive and statistically significant, signifying that, on the average, ICTs users adopted agroforestry technologies more than non-users in 1.744 times. It is therefore, clear that use of ICTs improves the adoption of agroforestry technologies that facilitate friendly environment. This is done in a way that the use of ICTs supports better access to information on agroforestry technologies' adoption and their benefits, which subsequently lead to rise in the rate of the technologies' adoption. This is the validation of the statement of Aker et al. (2016); Westermann et al. (2018) that ICTs have gained the attention of donor agencies as they are being used as tools in supporting transfer of knowledge and encouraging adoption and spread of innovations. On the average, the coefficients of years of education and household size are positive and statistically significant. The respective IRR estimates indicate that crop farmers who have higher number of years spent in school and higher household size adopted 1.020

and 1.065 times more agroforestry technologies, respectively. One of the possible reasons could be that well-educated crop farmers could easily search for information and decide based on their preferences using the collected information (Mahouna et al., 2018). Also, having large household members increased technology acceptance because agricultural technologies require more labour to practice (Adofu et al., 2013). Shita et al. (2020); Oparinde et al. (2023) reported that education had direct influence on the likelihood of adopting agroforestry technology.

The positive and significant IRR for the connection between farming experience and adoption of agroforestry technologies indicates that crop farmers with more experience tend to adopt agroforestry technologies more in 1.016 times on the average. This is in line with Ainembabazi and Mugisha (2014) who stated that farming experience plays significant roles in the adoption of agricultural technology. This could be ascribed to the on-the-job skills development over time that makes farmers to fit well into the new technology being taken to them for adoption. The direct and significant IRR of cooperative membership and credit constraints suggests that crop farmers who are members of cooperative society and non-credit constrained are more likely to adopt agroforestry technologies more in 1.240 and 1.154 times, respectively. The possible reason for the relationship between cooperative membership and number of agroforestry technologies adopted is that cooperative society plays financial and advisory roles that enhance adoption of agricultural technologies. Finding from this study confirmed the report of Wossen et al. (2017) where it was reported that cooperative society had an increasing effect on technology adoption through the provision of market information. The relationship that exists between credit constraints and agroforestry technologies' adoption could be because of the liquidity effects which lowers the issue of capital shortage that hinders investment in improved technologies. Abate et al. (2016) had also reported that farming households' access to credit raises the rate of agricultural technology adoption.

There is a direct and significant connection between land rights variable and agroforestry technologies' adoption. The positive and significant IRR of land rights indicate that having "use and transfer rights" would make crop farmers to adopt 1.365 times more agroforestry technologies than their colleagues who had "use only rights". This is expected because crop farmers who have "use and transfer rights" will be willing to invest in agroforestry technologies since they are aware of the long-term gains connected to the adoption of the technologies. This is in agreement with Owombo and Idumah (2017) where it was reported that landownership positively increased the probability of adopting agroforestry technology.

Treatment effects of ICTs use on agroforestry technologies' adoption

The treatment effects of ICTs use on agroforestry technologies adoption from ETPR model are presented in Table 4. ATE and ATT cannot be interpreted directly because they are not the same as IRR. The IRR of ICTs use on the number of agroforestry technologies adopted in Table 3 is presented from the perspective of marginal analysis. The significant estimated ATE of ICTs use on the number of agroforestry technologies adopted is 0.432, which implies that an average crop farming household will adopt 0.432 more agroforestry technologies when ICTs are used by such household. Also, the significant estimated ATT of ICTs use on the number of agroforestry technologies adopted is 0.477. This indicates that the average crop farming household in the ICTs user's category (that is, treated category) will adopt 0.477 more of agroforestry technologies than such household would if it did not use ICTs. It can be generally stated that ICTs use promotes adoption of agroforestry technologies in Southwest, Nigeria.

ATE	Z-value	ATT	Z-value
0.432	2.03	0.477	2.06

Source: Author's estimations based on data from survey 2022

Table 4: Treatment effects of ICTs use on agroforestry technologies' adoption from ETPR model.

Estimates from UQR for the joint effects of ICTs use and agroforestry technologies' adoption on revenue and HFIAS

Impact of ICTs use and agroforestry technologies' adoption on revenue and HFIAS from Unconditional Quantile Regression model estimates is presented in Table 5. For better understanding, Equations 1 and 2 were estimated simultaneously using seemingly unrelated regression equation (SURE) model in order to predict ICTs use and agroforestry technologies' adoption variables. In the estimation process, ICTs use was not included in Equation 2 for the purpose of avoiding issue of autocorrelation of the predicted ICTs use and agroforestry technologies' adoption. In line with Mishra et al.

(2015) and Ma and Wang (2020), $v_i = [\exp(\beta_i) - 1]$ is used to measure the proportional impact of dummy variables (Sex, Cooperative membership, Credit constraints and non-farm income) on farm revenue and HFIAS, where v_i and β_i represent proportional impact and coefficient of the variable, respectively. From this perspective, it is believed that the estimates give a descriptive comparison of the farm revenue and HFIAS for the households. The claim is not that the estimates possess a causal interpretation.

The estimates in Table 5 indicates that ICTs use and agroforestry technologies' adoption statistically and heterogeneously influenced farm revenue and HFIAS. Precisely, ICTs use had positive and significant association with farm revenue at the 25th and 75th quantiles with the uppermost influence of ICTs use on farm revenue occurring at the lowest quantile. This result confirmed the finding of Zhu et al. (2020) where it was stated that ICTs adoption brought about increase in farm income. There is an inverse relationship between ICTs use and HFIAS at the 50th quantiles, suggesting that use of ICTs by the crop farmers would improve their food security status since reduced HFIAS implies better food security status. These results validated the statement of Voss et al. (2021) that ICTs allow farmers to have access to a more comprehensive set of information and technologies capable of increasing productivity, improving market access, and contributing to household revenue and food security. Adoption of agroforestry

Variables	Farm revenue			HFIAS		
	25th	50th	75th	25th	50th	75th
Predicted ICTs Use	0.171*** (5.33)	-0.263 (1.05)	0.143*** (2.95)	0.047 (0.06)	-0.868** (1.97)	-0.417 (0.60)
Predicted Agroforestry Technologies Adoption	0.006*** (3.21)	-0.561 (1.32)	0.010 (0.02)	-0.969* (1.93)	-0.515 (0.68)	-0.958*** (2.74)
Sex	0.086 (0.71)	0.028 (0.21)	0.107*** (2.52)	-0.429 (0.99)	-0.189* (1.80)	0.260 (0.70)
Age	0.023 (0.08)	-0.001 (0.07)	0.010 (0.84)	-0.064*** (2.49)	0.003 (0.24)	0.050** (2.28)
Years of education	0.008 (0.73)	0.016*** (3.29)	-0.006 (0.34)	-0.028 (0.69)	-0.047** (2.17)	-0.038 (1.13)
Household size	0.023 (0.74)	0.057 (0.76)	0.060 (1.12)	0.383*** (3.35)	0.200*** (3.26)	-0.113 (1.15)
Farm size	-0.019 (0.51)	0.032 (0.76)	0.126** (1.97)	-0.183 (1.35)	-0.003 (0.04)	-0.236** (2.03)
Farming experience	-0.004 (0.19)	0.012 (0.49)	0.090*** (2.42)	-0.150* (1.91)	0.022 (0.53)	-0.001 (0.01)
Hours spent on farm	0.024 (0.98)	-0.034 (1.26)	-0.066 (1.58)	-0.068 (0.76)	-0.122*** (2.55)	-0.020 (0.27)
Extension visits	0.014 (0.37)	0.023*** (4.53)	0.060 (0.88)	-0.033 (0.23)	0.147* (1.93)	0.371*** (3.06)
Cooperative membership	0.113** (1.98)	0.225* (1.77)	0.090 (0.46)	-0.809* (1.94)	0.278 (1.24)	-0.071 (0.20)
Credit constraints	-0.118 (0.59)	-0.094 (0.43)	0.501*** (2.47)	-0593 (0.82)	-0.257** (5.66)	0.249 (0.40)
Non-farm income	0.179 (1.01)	0.343* (1.79)	0.966*** (3.16)	0.804 (1.62)	-0.378*** (2.81)	-0.598 (1.08)
Constant	12.314 (27.24)	12.662 (25.36)	11.875 (15.31)	20.938 (12.77	17.222 (19.48)	16.017 (11.41)
Observation	488			488		

Note: Standard errors in parentheses; ***P < 0.01, **P < 0.05, *P < 0.1. The mathematical expression $v_i = [\exp(\beta_i) - 1]$ cannot be used directly to calculate the proportional impact of the predicted ICTs use variable and agroforestry technologies' adoption variable on farm revenue and HFIAS since the two variables are used in the UQR model estimations.
Source: Author's estimations based on data from survey 2022

Table 5: Impact of ICT Use and agroforestry technologies' adoption on revenue and HFIAS from Unconditional Quantile Regression model estimates.

technologies positively and significantly influenced farm revenue at the 25th quantile, indicating that agroforestry technologies positively contribute to farm revenue. The results of Rola-Rubzen et al. (2019) has just been confirmed in this study, that adoption of agricultural technologies increases farm income. Household food insecurity access scale (HFIAS) is negatively influenced by adoption of agroforestry technologies at the 25th and 75th quantiles with the uppermost effect of agroforestry technologies' adoption on HFIAS at the 25th quantile. This indicates that the more the number of agroforestry technologies adopted the better the food security status of the respondents. It was earlier reported by Ogundari and Bolarinwa (2019) that agricultural technologies have increasing effects on household welfare measured in terms of nutrition.

Sex has a direct and significant nexus with farm revenue at the 75th quantile, while it has an indirect and significant association with HFIAS at the 50th quantile. This suggests that being male crop farmers brings about increase in farm revenue by about 11.29% (v_i = [exp(0.107)-1]) at the 75th quantile but decrease in HFIAS (that is, reduced household food insecurity) by around 20.80% (v_i = [exp(0.189) - 1]) at the 50th quantile. The positive relationship between sex and farm revenue could be linked to better access to productive resources by male farmers than their female colleagues. Zhu et al. (2020) reported similar results in the study carried out among rural farmers of China. Also, the negative relationship between sex and HFIAS supports the finding of Oparinde (2021) where it was reported that male aquaculture farmers were more food secure than their female colleagues. Age of respondents contributed negatively and significantly to HFIAS at the 25th quantile but had a positive and significant relationship with HFIAS at the 75th quantile. This indicates that increase in age of respondents reduced the level of food insecurity by 6.4% at the 25th quantile but increased the level of food insecurity by 5.0% at the 75th quantile. The increasing effect could be attributed to old age when farmers would not be agile enough to get involved in farming activities being energy sapping in nature. This is in line with Ajayi and Olutumise (2018) who reported that older farmers had higher probability of being food insecure. Years of education variable had positive and negative significant correlation with farm revenue and HFIAS at the 50th quantile, respectively, indicating that increase in number of years spent in school will improve farm revenue by 1.6% and reduce level of food insecurity of the crop farming household by 4.7%. Similar result was reported by Oparinde (2019) who stated that increase in years of education raised the likelihood of farmers being food secure, while Zhu et al. (2020); Zhang (2020) reported that education increased farm income.

The coefficient of household size was positive and significant at 25th and 50th quantiles, suggesting that household size increased HFIAS by 38.3% and 20.0% at 25th and 50th quantiles, respectively. The implication of this is that increase in family size would increase the level of food insecurity among the respondents. The results further confirmed the finding of Oparinde (2019) that household size increased food insecurity. Farm size increased farm revenue by 12.6% and reduced HFIAS by 23.6% at the 75th quantile, which implies that crop farmers with higher farm size would have more farm revenue and improved food security status. Shahzad and Abdulai (2020) also reported that level of food insecurity declined as a result of increased farm size in Pakistan, while Liu et al. (2019) stated that larger farm size contributes significantly to farm income. Farming experience positively contributed to farm revenue and negatively contributed to HFIAS at the 75th and 25th quantile, respectively. This suggests that more farming experience increased farm revenue but reduced level of food insecurity among crop farming households. Ahmed et al. (2015) stated that there may be increase in the level of food insecurity because of reduced production and revenue triggered by inadequate farming experience. Number of extension visits contributed significantly to farm revenue at the 50th quantile. This result supports various findings in the literature. For example, Anang et al. (2020) reported that agricultural extension had a statistically significant influence on farm income in Northern Ghana.

Cooperative membership had a direct and significant connection with farm revenue at the 25th and 50th quantiles but indirect and significant influence on HFIAS at the 25th quantile. This shows that members of cooperative society(ies) would have higher revenue by about 11.96% (v_i = [exp(0.113)-1]) and 25.23% (v_i = [exp(0.225)-1]) at the 25th and 50th quantile, respectively. However, members of cooperative society(ies) would have lower HFIAS (higher level of food security) by around 124.57% (v_i = [exp(0.809)-1]) at the 25th quantile. Similar result was gotten by Kabunga et al. (2014) where cooperative membership was observed to have positively influenced farm income.

Credit constraints variable positively and significantly influenced farm revenue at 75th quantile while the same variable negatively and significantly influenced HFIAS at 50th quantile. The implication of this is that non-credit constrained crop farming households realized higher farm income than credit constrained crop farming households by about 65.04% (v_i = [exp(0.501)-1]) at the 75th quantile, while the HFIAS reduced (that is, reduced level of food insecurity) by around 29.30% (v_i = [exp(0.257)-1]) among non-credit constrained crop farming households at the 50th quantile. Shahzad and Abdulai (2020) reported similar result which states that credit constrained farmers had higher HFIAS (that is, increase in level of food insecurity) than their non-credit constrained counterparts. Non-farm income had a direct and significant effect on farm revenue at the 50th and 75th quantile, while it had a negative and significant influence on HFIAS at the 50th quantile. This implies that crop farmers who have non-farm income realized more farm revenue by about 40.92% (v_i = [exp(0.343)-1]) at the 50th and about 162.74% (v_i = [exp(0.966)-1]) at the 75th quantile. Crop farmers with non-farm income had lower HFIAS by about 45.93% (v_i = [exp(0.378)-1]) at the 50th quantile. The probable reason for the association between non-farm income and HFIAS could be the income effect of participating in non-farm activities which can raise farmers' income that helps in improving household food security (Twumasi et al. (2021). This result establishes the finding of Abdullah et al. (2019).

Conclusion

This study analysed the impact of ICTs use on agroforestry technologies' adoption with the use of ETPR model which accounts for the likely selection bias owing to the unobservables related to ICTs use. Also, UQR model was used to examine the heterogenous impact of ICTs use and agroforestry technologies' adoption on farmers' welfare (farm revenue and HFIAS). The results indicated that the use of ICTs improved the adoption of agroforestry technologies that facilitate friendly environment. Specifically, ICTs users adopted agroforestry technologies more than non-users in 1.744 times on the average. The ATT and ATE results indicated that ICTs use promotes adoption of agroforestry technologies in the study area. Also, ICTs use and agroforestry technologies' adoption statistically and heterogeneously influenced farm revenue and HFIAS. Precisely, ICTs use had positive and significant association with farm revenue at the 25th and 75th quantiles with the topmost influence of ICTs use on farm revenue occurring at the lowest quantile. There is an inverse relationship between ICTs use and HFIAS at the 50th quantiles, suggesting that use of ICTs by the crop farmers would improve their food security status since reduced HFIAS implies better food security status. Adoption of agroforestry technologies positively and significantly influenced farm revenue at the 25th quantile, indicating that agroforestry technologies positively contribute to farm revenue. Household food insecurity access scale (HFIAS) is negatively influenced by adoption of agroforestry technologies at the 25th and 75th quantiles with the uppermost effect of agroforestry technologies' adoption on HFIAS at the 25th quantile.

Therefore, it is suggested that policies that promote crop farmers' access to ICTs should be the priority of policy makers who are interested in the welfare of crop farmers and increased farmers' level of agroforestry technologies' adoption. This is important since ICTs use improved the agroforestry technologies' adoption, farm revenue and food security status of the crop farmers. Also, policy measures aimed at encouraging the adoption of agroforestry technologies should be the top agenda of government and other stakeholders who are conscious of friendly environment and crop farmers' welfare since adoption of agroforestry technologies improved farm revenue and food security status among farmers. Having seen that cooperative membership significantly contributed to agroforestry technologies' adoption, farm revenue and food security, cooperative societies, as a matter of policy, should be included in the government's and other stakeholders' efforts to promote agroforestry technologies adoption and other welfare related programmes. Credit conditions of crop farmers should be improved through availability of single-digit-interest credit facilities that will enable them to use ICTs and adopt agroforestry technologies. This is necessary because ICTs use and agroforestry technologies require certain level of financial investments and credit constraints variable significantly influenced the use of ICTs adoption of agroforestry technologies. Years of education variable positively contributed to ICTs use, agroforestry technologies' adoption and welfare of crop farmers in the study area. Therefore, investment in education (formal or informal) should form part of the policy measures meant to promote ICTs use, adoption of agroforestry technologies, farm revenue and food security status of crop farmers. Now that the results from this study are interesting, further studies should focus on the impact of each of the agroforestry technologies on farmers' welfare in order to avoid loss of information on the roles of each of the technologies in farmers' welfare improvement.

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Appendix

	ICTs use	Agroforestry technologies' adoption
	0.2659 (0.000)	(0.0176) (0.1521)

Notes: Figures in brackets are the p-values
Source: Author's estimations based on data from survey 2022

Appendix 1: Pearson correlation test results for the validity of the instrumental variable.