The Average and Distributional Impacts of Soil and Water Conservation Technologies on the Welfare of Smallholder Farmers in Tanzania

by Julius Manda, Adane H. Tufa, Arega D. Alene, Elirehema Swai, Francis Muthoni, Irmgard Hoeschle-Zeledon, and Bekunda Mateete

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Using recent survey data from over 500 sample households, this study evaluates the adoption and welfare impacts of soil and water conservation technologies (SWCT) in Tanzania. We apply the endogenous switching regression (ESR) and endogenous switching probit (ESP) models to estimate the average impacts and the instrumental variable quantile treatment effects (IVQTEs) to analyses the distributional impacts of adoption. The results show that the adoption of SWCT increased household income by an average of 49%. Moreover, we find that adoption had a significant and positive effect on the food security and micronutrient consumption indicators—household dietary diversity (HDD), household food insecurity access scale (HFIAS), consumption of iron and vitamin-rich foods. The IVQTEs show that the impacts of adopting SWCT on the outcome variables are positive and significant, although they vary significantly across the welfare distribution. The results also show that even though adoption benefits both the poor and non-poor households, the marginal impacts of adoption are larger for the households with the highest as compared to those with the lowest household welfare levels. The paper concludes with a discussion of the policy options for increasing adoption and impacts of SWCT in Tanzania.

Keywords: Soil and water conservation technologies; income; food security; Tanzania.

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Introduction

Soil nutrient deficiency and moisture stress have been identified as the major factors limiting crop productivity in many parts of sub-Saharan Africa (Mueller et al., 2012). These problems are often exacerbated where agricultural production is predominantly dependent on seasonal rainfall and is characterized by low use of fertilizer and soil and water conservation technologies (SWCT) that would reduce soil fertility loss through erosion. The dependence on rain-fed agriculture exposes farmers to climatic risks such as droughts and this can dramatically reduce crop yields and livestock production (Schmidhuber and Tubiello, 2007), especially in semi-arid regions.

In the last four decades, Tanzania has experienced a series of severe droughts and floods which have increased the uncertainty in seasonal rainfall prediction (FAO, 2014). This has had negative effects on crop productivity, especially in the semi-arid region of central Tanzania. Coupled with this, soil erosion resulting from inappropriate crop management practices, tillage and livestock grazing systems have led to reduced crop productivity due to loss of soil organic matter and soil nutrients. In response to these problems, the International Institute of Tropical Agriculture (IITA) and its partners through the Africa Research in Sustainable Intensification for the Next Generation (Africa RISING) program has been testing and promoting sustainable intensification practices to increase crop and livestock productivity, incomes, and nutrition among smallholder farmers while mitigating the adverse effects on the environment. One of the sustainable intensification practices that have been promoted to arrest declining soil fertility is the integrated soil fertility management (ISFM) with its local adaptations such as SWCT[2]. However, there is limited empirical evidence on the extent and impacts of the adoption of SWCT in Tanzania.

While there is a large body of literature on the productivity and income effects of the adoption of SWCT (e.g. Di Falco et al., 2011; Di Falco and Veronesi, 2013; Kassie et al., 2008; Kassie et al., 2011; Abdulai and Huffman, 2014), there are relatively few studies that have examined the relationship between SWCT and food/nutrition security (Issahaku and Abdulai, 2019; Habtemariam et al., 2019). Previous research has demonstrated a linkage between the adoption of improved crop varieties and dietary diversity/specific nutrient consumption (Mumin

[2] See Vanlauwe et al., (2015, 2011) for more details on ISFM.

and Abdulai, 2021; Smale et al., 2015). However, empirical evidence on the impact of SWCT on micronutrient consumption among rural households is especially lacking in the literature. To our knowledge, the study by Kim et al. (2019) is one of the few studies that have examined the relationship between the adoption of sustainable intensification practices and child nutrition. However, this study did not consider SWCT and only used children nutritional outcomes. Moreover, most of the previous studies have assumed that the welfare impacts of the adoption of SWCT are homogenous, ignoring the fact that the returns to the adoption of most agricultural innovations in sub-Saharan Africa are heterogeneous (e.g. Suri, 2011; Zeng et al., 2015; Wossen et al., 2018b). This study aims to fill this gap in the literature by examining the average and distributional impacts of the adoption of SWCT on income and several indicators of food security and nutrient consumption i.e. household income, household dietary diversity (HDD), household food insecurity access scale (HFIAS), consumption of iron and vitamin A-rich foods and subjective food security.

We contribute to the growing literature on SWCT in the following ways. First, unlike previous studies e.g. Kassie et al. (2011, 2008) and Abdulai and Huffman (2014), we estimate the impact of adoption on HDD, HFIAS, consumption of iron and vitamin A-rich foods and subjective food security in addition to the income indicator. These indicators measure the quantity and quality of food access at the household level and also have an element of household nutrition. For example, HDD is associated with diet quality since it helps ensure adequate intake of essential nutrients and promotes good health (Leroy et al., 2015). The HFIAS is based on subjective responses to questions which capture universal aspects of the experience of food insecurity, information on food shortage, food quantity and quality of diet to determine the status of a given household's access to food (Carletto et al., 2013). The consumption of iron and vitamin A-rich foods are two additional outcome indicators we use to test the relationship between adoption of SWCT and nutrition. Deficiencies in these micronutrients are responsible for major health problems in developing countries (Ogutu et al., 2019). For the last measure of food security, we use respondents' perceptions about their food security status as an additional subjective food security indicator. The use of subjective food security indicators helps to check for consistency of the other indicators with farmers' assessment of their food security status during the whole year, after accounting for seasonal shocks (Shiferaw et al., 2014). Second, we examine the distributional effects of the adoption of SWCT using the instrumental variable unconditional quantile treatment effects (IVQTEs) model. Most of the previous studies have either used conditional quantile treatment effects (QTEs) (e.g. Issahaku and Abdulai, 2019; Ogutu and Qaim, 2019) or unconditional treatment effects without controlling for unobservable characteristics (e.g. Ainembabazi et al., 2018; Mishra et al., 2015). According to Frölich and Melly (2013, 2010), unlike the conditional QTEs which changes with the set of conditioning covariates, the unconditional QTEs don't depend on other covariates to be consistently estimated. The second advantage of unconditional effects is that they can be estimated consistently without any parametric restrictions, which is not possible for conditional effects. We also complement the IVQTEs results with the SD method which only accounts for observed factors to examine how treatment effects vary with the propensity to adopt SWCT.

The rest of the article is organized as follows: The next section describes the data and descriptive statistics, while section 3 presents the empirical framework. Section 4 presents the results and discussion, and the last section draws conclusions and policy recommendations.

1. Data and descriptive statistics

The data used in this paper come from a survey of 580 sample households conducted between September and October 2020 in the semi-arid districts of Kiteto and Kongwa in central Tanzania. A survey questionnaire was prepared and designed in Surveybe, a computer-assisted personal interviewing (CAPI) software, and administered by trained enumerators who collected data from households through personal interviews.

A multistage random sampling procedure was used to select sample households. In the first stage, five wards (Oluboloti, Njoro, Mlali, Nghumbi and Sagara) were purposively selected from the two Africa RISING project districts where there has been active testing and promotion of SWCT. In the second stage, five villages from the five wards were selected using probability proportional to size sampling (PPS). With the help of the ward extension agents, and Tanzania Agricultural Research Institute (TARI), a sampling frame was developed by listing all households (including adopters and non-adopters of SWCT). In the final stage, 120 households were randomly selected from each village resulting in 240 households from Kiteto district and 360 households from Kongwa district. However, 340 households were interviewed in Kongwa district because the remaining 20 households could not be traced.

Detailed information was collected on demographic and socioeconomic characteristics (e.g. household head's age, sex, and education; livestock ownership), farm characteristics (e.g. farm size, farmers' perception of the slope and fertility of their land), and household income. Table 1 shows the definition and summary statistics of the variables used in this study. The results show that, on average, 22% adopted SWCT in 2019/2020 growing season. In this paper, we define SWCT as either tied ridging or fanya-juu terraces. A farmer is considered to have adopted if they used SWCT in the 2019/2020 growing season. Tied ridging is an *in-situ* rainwater harvesting technique that collects rainwater in the field to facilitate water infiltration, subsequently increasing crop productivity (Habtemariam et al., 2019). It involves blocking ridge furrows with earth ties spaced at a fixed distance apart to form a series of micro-catchment basins in the field (Wiyo et al., 2000). The use of fanya-juu terracing system also has the potential to reduce water runoff, soil erosion, and siltation of rivers, lakes and dams and thus improves soil infiltration, fertility and crop yields (Saiz, et al. 2016; Kassie et al., 2011). Fanya-juu' terracing system consists of constructing embankments along a slope by digging out trenches following contour lines and depositing the soil uphill of the trench to form a mound.

We use four outcome variables; household income, HDD, HFIAS and subjective food security to proxy household welfare. Household income is a reliable indicator of economic well-being among smallholder farmers and includes income from crops, livestock and livestock products, and off-farm income (e.g. salaries, remittances, farm labour wage income, pension income and income from businesses).

To measure food security, we generated HDD scores and constructed the HFIAS. HDD was initially developed as an indicator of the quantity and quality of food access at the household level (Leroy et al., 2015). Apart from being a measure of household access to a variety of foods, it is also a proxy for diet quality. Some studies (e.g. Magrini and Vigani, 2016), have used HDD to measure the food utilization dimension of food security. In this study, we used HDD scores (HDDS) as an indicator of HDD (Kennedy et al, 2010). During the survey, households were asked to mention the food items they consumed in the 24 hours, and these included Cereals, white roots and tubers, vitamin A-rich vegetables and tubers, dark green rich vegetables, other vegetables, vitamin A-rich fruits, other fruits, organ meat, flesh meats, eggs, fish and seafood, legume, nuts and seeds, milk and milk products, oil and fats, sweets and spices. Following Kennedy et al. (2010), we combined the vegetables, meats and fruits such that we had 12 food groups, each with a score of 1 if they consumed a food item. The HDDS were then constructed by summing these food groups such that the scores ranged from 0-12. The HFIAS uses a set of questions that represents universal domains and subdomains of experiencing household food insecurity and lack of access to food (Leroy et al., 2015). The scale was developed through the Food and Nutrition Technical Assistance Project (FANTA) and details on how it is constructed are outlined in Coates et al. (2007). The HFIAS ranges from 0-27, so that the higher the score, the more food insecurity the household experienced, and the lower the score, the less food insecurity a household experienced. From the food groups mentioned above, we categorized iron-rich foods as organ meat, flesh meat, or fish and vitamin A-rich foods like organ meat, eggs or milk and milk products following Kennedy et al. (2010). Finally the subjective binary food security measure was generated using the respondents' perception of their food security situation. Respondents were asked how they perceived their food security situation in the year before the survey, based on their food production, food purchases, and aid from different sources. The respondents categorized their household food security status in either food secure or food insecure.

Table 1 also shows several demographic and socio-economic variables that are hypothesized to affect the adoption of SWCT. Household characteristics such as age, sex and education of the household head; and socio-economic characteristics such as access to credit, livestock ownership, access to off-farm income and labour are important determinants of agricultural innovations (Feder and Umali, 1993; Feder et al., 1985; Kassie et al., 2013). The number of years a household head has lived in the village, having friends or relatives in leadership positions and membership in farmer organizations are meant to capture social capital and networking (Kassie et al., 2013; Abdulai and Huffman, 2014). Farm characteristics which have been shown to affect the adoption of SWC technologies include farm size, adoption of improved crop varieties, perceptions on the slope and soil fertility of the land (Abdulai and Huffman, 2014; Amsalu and de Graaff, 2007; Kassie et al., 2008). We also constructed a rainfall index following Teklewold et al. (2013) and Kassie et al. (2013) based on questions such as whether rainfall came and stopped on time, whether there was enough rain at the beginning and during the growing season, and whether it rained at harvest time in the preceding three seasons. We constructed the rainfall index using principal component analysis (PCA). We specifically used the first principal component since it explains the most variance in the data as opposed to multiple components. The factor scores from the first component were used as weights for each question to construct the indices for each household.

Table 1: Variable names, definitions, and descriptive statistics for the sample

Variables	Definition	Mean	SD
Treatment variable			
Adoption	1= If a household adopted SWCT, 0 otherwise	0.218	0.413
Outcome variables			
Household income	Household income per capita (Tsh)	223,560	227,222
HDDS	Household Dietary Diversity Scores (number)	6.289	2.203
HFIAS	Household food insecurity access scale (number)	3.759	5.260
Iron	1 if households consumed organ meat, flesh meat, or fish, 0 otherwise	0.420	0.413
Vitamin A	If households consumed organ meat, eggs or milk and milk products, 0 otherwise	0.219	0.494
Subjective food security	1 = Household is food secure, 0 otherwise	0.443	0.497
Independent variables			
Age	Age of the household head (years)	49.15	13.42
Sex	1= Household head is male, 0 otherwise	0.752	0.432
Education	Education of the household head (years)	1.321	2.788
Farm size	Total land owned by the household (ha)	2.889	4.805
Household size	Total household size (number)	5.568	2.199
Contacts	Number of contacts with extension agents	5.955	11.76
Credit	1= Received credit, 0 otherwise	0.0487	0.215
Livestock	Livestock ownership in Tropical Livestock Units (TLU)	1.085	2.664
Off-farm	1= Access to off-farm income, 0 otherwise	0.385	0.487
Leadership	1= Household has friends/relatives in leadership position, 0 otherwise	0.365	0.482
Labour	Hired labour in man-days	59.15	179.9
Years	Years the household head has lived in the village	36.97	17.00
Improved variety	1= proportion of households who used improved crop variety, 0 otherwise	14.600	0.353
Slope	The proportion of land on a steep slope (%)	2.95	0.169
Soil fertility	The proportion of land with fertile soils (%)	19.8	0.399
Rainfall	Rainfall index	-0.001	1.399
Distance capital	Distance in walking minutes to the district capital	241.7	53.60
Instrumental variables			
Membership	1= Member of an a formal/informal farmer group	0.282	0.451
Neighbor	1= Neighbor/friend is an adopter of SWC technologies	0.847	0.360

Table 2 presents the descriptive statistics for our sample, disaggregated by whether or not households adopted SWCT along with balancing tests. We find statistically significant differences between adopters and non-adopters for most of the control variables. Adopters tend to have larger household sizes and more contacts with extension agents than non-adopters. Furthermore, most of the adopters of SWCT have better access to credit (10%), grow improved crop varieties (4%), and have more networks and social capital as compared to non-adopters. Results show that adopters are also distinguishable in terms of farm characteristics. They perceive their land to be steeper (7%) and more fertile (3%) as compared with the non-adopters. Although these results show significant differences, they do not account for observed and unobserved characteristics, an issue we address in the subsequent sections.

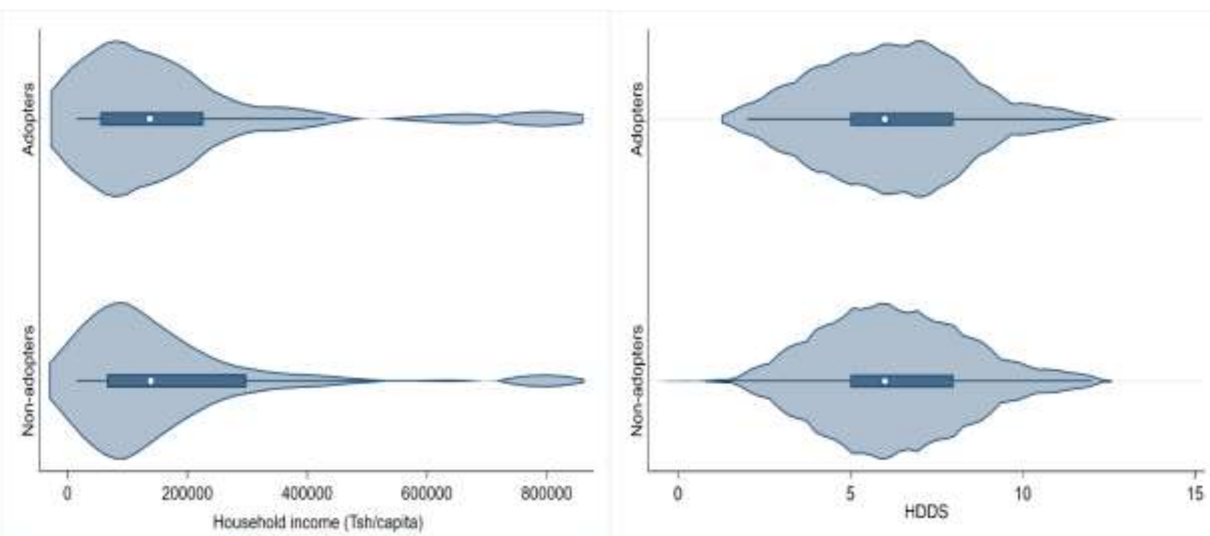
Table 2: Descriptive statistics by adoption status of SWCT and balance tests

Variable	Adopted SWCT?		Difference
	No	Yes	
Household income	287206.3	273961.5	
	(11069.034)	(19483.840)	
HDDS	6.302	6.246	
	(0.104)	(0.193)	
HFIAS	3.680	4.040	
	(0.246)	(0.479)	
Iron	0.416	0.444	
	(0.023)	(0.044)	
Vitamin A	0.20	0.294	**
	(0.018)	(0.041)	
Subjective food security	0.436	0.468	
	(0.023)	(0.045)	
Age	48.863	50.167	
	(0.640)	(1.138)	
Sex	0.778	0.659	***
	(0.020)	(0.042)	
Education	1.242	1.603	
	(0.128)	(0.267)	
Farm size	2.935	2.724	
	(0.233)	(0.377)	
Household size	5.443	6.016	***
	(0.099)	(0.222)	
Contacts	3.783	13.730	***
	(0.437)	(1.408)	
Credit	0.036	0.095	***
	(0.009)	(0.026)	
Livestock	1.007	1.363	
	(0.123)	(0.252)	
Off-farm	0.388	0.373	
	(0.023)	(0.043)	
Leadership	0.334	0.476	***
	(0.022)	(0.045)	
Labour	59.778	56.897	
	(8.892)	(12.832)	
Years	36.773	37.675	
	(0.788)	(1.612)	
Improved variety	0.064	0.437	***
	(0.012)	(0.044)	
Slope	0.022	0.056	*
	(0.007)	(0.020)	
Soil fertility	0.171	0.294	***

	(0.018)	(0.041)	
Rainfall	0.068	-0.247	**
	(0.059)	(0.160)	
Distance capital	239.820	247.032	
	(12.587)	(13.050)	
Membership	0.202	0.571	***
	(0.019)	(0.044)	
Neighbour	0.820	0.944	***
	(0.018)	(0.020)	

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors appear in parentheses. *t*-tests are the differences in the means across the groups.

To gain further insight into the distribution of the continuous outcome variables, figure 1 shows violin plots by the adoption status. Violin plots combine the basic summary statistics of a box plot with the visual information provided by a local density estimator to reveal the distributional structure in a variable. Figure 1 shows significant heterogeneity with groups of households clustering in upper and lower tails of the distributions, suggesting that adoption of SWCT might unduly affect less productive and underprivileged households. This justifies the use of IVQTE to further explore the distributional impacts of the adoption of SWCT in section 4.



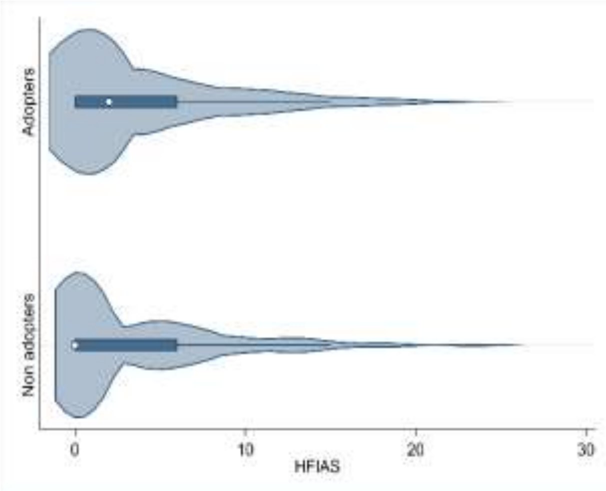


Figure 1: Violin plots of household income, HDDS and HFIAS

2. Conceptual and empirical frameworks

3.1 The endogenous switching probit model

The frequent occurrence of droughts and floods affects crop production, lives, health, livelihoods, assets and infrastructure that contribute to food insecurity and poverty among smallholder farmers in sub-Saharan Africa (Shiferaw et al., 2014). The adoption of SWCT offers a potential solution to these problems by reducing water runoff and soil erosion, and increasing soil fertility thereby enhancing crop productivity and farm incomes of smallholder farmers. It is therefore expected that the adoption of SWCT will lead to an increase in crop yields and consequently the availability of more diversified food for the household. Then again, crop productivity increases through the adoption of SWCT will increase the marketable surplus which is expected to increase household income. Ultimately, it is envisioned that this will result in increased expenditure on diverse, high calorie and protein foods, finally leading to improvement in household food security and nutrition. As mentioned earlier, the impact of SWCT on crop productivity is well established in the literature, both from on-farm trials and plot-level surveys (e.g. Kassie et al., 2008; Kato et al., 2011; Tsubo et al., 2005). In this study, we envisage that the adoption of SWCT will mainly increase household incomes, food security and nutrition through the crop productivity impact pathway.

The challenge, therefore, is to estimate the causal effect of the adoption of SWCT on household income and food security, as this is not trivial, especially with non-experimental data.

In the ensuing sections, we use "household welfare" to mean household income and food security. One way to achieve this would be to regress the adoption variable on the welfare indicator variables with household and farm characteristics added as controls. Yet, because farmers actively self-select into the adoption category based on their potential gains, endogeneity problems may arise leading to biased estimates (Abadie and Cattaneo, 2018; Alene and Manyong, 2007). If the assumption is that the adoption of SWCT has an average impact on household welfare, then instrumental variable (IV) regression which measures intercept shifts, i.e. average effects, can be used to account for endogeneity. However, household and farm characteristics can also lead to an improvement in household welfare by way of slope shifts in the household welfare production function. These effects are not captured by an IV type of regression. To properly account for endogeneity and the differential effects on adopters and non-adopters, we use the endogenous switching regression (ESR) and endogenous switching probit (ESP) models (Lokshin and Sajaia, 2011; Fuglie and Bosch, 1995; Lee, 1978). In this approach, the adoption decision is modelled using a probit model, while two separate outcome equations for adopters and non-adopters are specified. Since the modelling of the ESR and ESP models is similar, we only present the details for the ESP model[3].

To set the stage for our estimation strategy, we view the decisions of a farmer to adopt SWCT in a given period to be derived from the maximization of expected utility subject to land availability, credit, and other constraints (Feder et al., 1985). A farmer will adopt if $D_i^* = U_1 > U_0$, where U_1 is the expected utility arising from the adoption of SWCT and U_0 is the utility of non-adoption U_0. D_i^* is a latent variable that captures the expected benefits from the adoption choice and is determined by a set of exogenous variables, V_i and the error term μ_i:

$$D_i^* = V_i\alpha + \mu_i \text{ where } D_i = \begin{cases} 1 \; if D_i^* > 0 \\ 0 \; otherwise \end{cases} \qquad 1$$

where D is a binary indicator variable that equals 1 if a farmer adopts SWCT and zero otherwise and α is a vector of parameters to be estimated. Given that farmers choose to either adopt the

[3] The ESR model has been widely used in the literature, unlike the ESP model. For more details on the ESR model see, Abdulai and Huffman (2014) and Alene and Manyong, (2007) who give a good exposition of the model.

technology or not adopt it, the two outcome equations, conditional on adoption can be written as follows:

Regime 1 (Adopters): $y_{1i} = X_{1i}\beta_1 + \varepsilon_{1i}$ if $D_i = 1$ 2a

Regime 1 (Non-Adopters): $y_{2i} = X_{2i}\beta_2 + \varepsilon_{2i}$ if $D_i = 0$ 2b

Where y_{1i} and y_{2i} are the binary outcome variables (Iron, Vitamin A and subjective food security) for adopters and non-adopters respectively. X_{1i} and X_{2i} are vectors of weakly exogenous covariates, while β_1 and β_2 are parameters to be estimated for the adopter and non-adopter regimes respectively.

For the ESP model to be properly defined identified, the *Z* variables in the adoption model need to contain an instrument in addition to those automatically generated by the non-linearity of the selection model of adoption. The requirements for a valid instrument are that it significantly affects the adoption of SWCT conditional on covariates (relevance condition) and that it affects household welfare only through *D*, but not directly (exclusion restriction). We use neighbours' adoption decisions and group membership (Abdulai and Huffman, 2014; Bandiera and Rasul, 2006; Krishnan and Patnam, 2013) as identifying instruments. We checked whether our instruments were correlated with the adoption status (relevance condition) and the reported results in Table 2 show that the instruments are relevant. Several previous studies have used these instruments (e.g. Abdulai and Huffman, 2014; Kabunga et al., 2012; Wossen et al., 2018a, 2018b; Tufa et al., 2019).

The three error terms μ_i , ε_{1i} and ε_{2i} from equations 1, 2a and 2b are assumed to have a joint normal distribution with mean vector zero and correlation matrix:

$$\Omega = \begin{bmatrix} 1 & \rho_1 & \rho_2 \\ & 1 & \rho_{12} \\ & & 1 \end{bmatrix} \tag{3}$$

Where ρ_1 and ρ_2 are the correlations between the error terms u_i , ε_{1i} and ε_{2i} ,u_i and ρ_{12} is the correlation between of ε_{1i} and ε_{2i}. We assume that ρ_{12}=1 since α is estimable only up to a scalar factor. ρ_{12} is not defined because y_{1i} and y_{2i} are not observed simultaneously. This implies that the expected values of ε_{1i} and ε_{2i} conditional on sample selection are non-zero because the error term in the selection equation is correlated with the error terms in equations 2a and 2b and probit model estimates of coefficients β_1 and β_2 are biased. Sample selection bias arises when factors unobserved by the researcher but known to the farmer affect both the choice of technology and other decision variables (Fuglie and Bosch, 1995). Finally, the selection and outcome equations are estimated jointly using Full Information Maximum Likelihood (FIML) estimation procedure.

Following Aakvik et al. (2005) and Lokshin and Sajaia (2011), we can estimate the impact of adoption on the outcome variables for those who adopted SWCT —i.e. the average treatment effect on the treated (ATT) as follows:

$$ATT = E[Pr\,(y_1 = 1|D = 1, X = x] - E[Pr\,(y_2 = 1|D = 1, X = x]$$

$$= \quad \frac{\Phi_2(X_1\beta_1, V\alpha, \rho_1) - \Phi_2(X_2\beta_2, V\alpha, \rho_2)}{F(V\alpha)} \tag{4}$$

where Φ_2 is the cumulative function of a bivariate normal distribution and F is the cumulative function of the univariate normal distribution.

The ESP model described above can only be used for binary outcome variables, hence, to estimate the impact of adoption on the income, HDD and HFIAS, we use the ESR model. In the ESR, instead of estimating the outcome equations in 2a and 2b using a probit model, we use ordinary least squares regression (OLS)

3.2 The instrumental variable unconditional quantile treatment effects

The violin plots presented above suggest that the welfare effects of adoption are likely to be conditional on adopters' observed and unobserved characteristics. To estimate the distributional or heterogeneous effects of adopting SWCT, we use the IVQTE following Frölich and Melly (2013, 2010). The estimation of quantile treatment effects (QTE) is important to evaluate the effect of a variable on different points of the outcome distribution and therefore allows for the identification of effects even in situations where the mean of the outcome variable remains unchanged. Let y_{1i} and y_{0i} be the continuous potential welfare outcomes of household *i*. Hence, y_{1i} would be realized if individual *i* were to adopt SWC technologies (*D* =1), and y_{0i} would be realized otherwise. Following Frölich and Melly (2013, 2010), the unconditional QTE (for quantile τ) can generally be given by:

$$\Delta^{\tau} = Q_{y_1}^{\tau} - Q_{y_0}^{\tau} \qquad 5$$

where $Q_{y_1}^{\tau}$ is the quantile for y_{1i} and $Q_{y_0}^{\tau}$ is the τth quantile of y_{0i}.

As mentioned above, the decision to adopt is endogenous, hence the identification can only be achieved through an *IV*, *Z*. The treatment effects are allowed to be arbitrarily heterogeneous, such that the effects can only be identified for the population that responds to a change in the value of the instrument, i.e. compliers (Frölich and Melly, 2013). Therefore, we focus on the QTEs for the compliers:

$$\Delta^{\tau} = Q_{y1|c}^{\tau} - Q_{y0|c}^{\tau} \qquad 6$$

The unconditional IVQTE for compliers proposed by Frolich and Melly (2013) can be defined as a bivariate quantile regression estimator with weights:

$$\left(\hat{\alpha}_{IV}, \hat{\Delta}_{IV}^{\tau}\right) = \underset{\varphi\Delta}{\operatorname{argmin}} \sum W_i^{FM} \rho_{\tau}(y_i - \alpha - D_i\Delta) \qquad 7$$

where W_i^{FM} denote the weights proposed by Frolich and Melly (2008, 2013). $\rho_{\tau} = \mu\,\{\tau - 1(\mu < 0)\}$, where μ is the asymmetric absolute loss function or check function (Wooldridge, 2010). The weights are defined as:

$$W_i^{FM} = \frac{Z_i - \Pr(Z-1|X_i)}{\Pr(Z = 1|X_i)\{1-\Pr(Z=1|X_i)\}} \qquad 8$$

where Z_i is a binary instrumental variable and $\Pr(Z = 1|X_i)$ are the propensity scores[4].

As a key robustness check for the distributional impacts of adoption, we also estimate treatment heterogeneity by conditioning on a full set of covariates but without controlling for unobserved heterogeneity following Brand and Xie, (2010) and Xie et al. (2012). Besides, the QTEs described above are only valid for continuous outcomes, implying that it is not possible to estimate the heterogeneous effects for the micronutrient consumption and subjective food

[4] In the IVQTE model, only one instrument can be used, hence we use group membership as an identifying IV in the income and HDDS equations and; neighbours adoption decisions in the HFIAS equation.

security measures. Following Xie et al. (2012), we use the SD method to analyse how treatment effects vary with the propensity to adopt SWCT. In summary, the method follows three steps: First, we estimate the propensity scores using the same covariates (*V*) described in equation 1. Second, we fit separate, non-parametric regressions of the welfare variables on the propensity score for the adopters and non-adopters. Third, we estimate the difference in the non-parametric regression line between the adopters and non-adopters at different levels of the propensity score. This enables one to obtain ta pattern of treatment effect heterogeneity as a function of the propensity score.

3. Results and discussion

4.1 Determinants and impacts of the adoption of SWCT

The FIML estimates of the determinants of adoption of SWCT are shown in Table 3. These are the results emanating from the estimation of equation 1 using a probit model. For the sake of brevity, we do not present the second stage results but are availbe on request.

Consistent with Issahaku and Abdulai (2019), results show that female-headed households are more likely to adopt SWCT compared with male-headed households. The results also indicate that educated farmers are more likely to adopt SWCT as they might acquire new knowledge and process information more easily (Abdulai and Huffman, 2014; Adegbola and Gardebroek, 2007). We find that household size increases the probability of the adoption of SWCT by smallholder farmers in Tanzania. This is a common finding in studies investigating the adoption of labour-intensive technologies is that the size of the household is associated with an increase in the rate of adoption of such technologies (Kassie et al., 2008; Ojo and Baiyegunhi, 2020; Di Falco and Veronesi, 2013). One explanation advanced for this finding is that household size is a proxy for household labour endowments, especially in developing countries.

We also find that farm households with more contacts with extension agents have a higher propensity to adopt SWCT. In developing countries, extension agents are essential in the provision of information regarding improved agricultural technologies and therefore play an important role in determining farmers' decisions to adopt (Di Falco et al., 2011; Di Falco and Veronesi, 2013). The results further reveal that the adoption of SWCT increases with the adoption of improved crop varieties, a finding consistent with that of Abdulai and Huffman (2014). Most of the SWCT activities are concentrated in Kongwa district, implying that farmers in this district receive relatively more support services such as extension, group membership and other farmers who have adopted these technologies. This evidenced by the significant coefficient on the Kongwa dummy which shows that farmers in Kongwa are more likely to adopt SWCT compared to those in Kiteto district. The neighbours' adoption decisions and membership in a farmer's organization increase the probability of adopting SWCT and this also shows that they are relevant instruments in identifying our ESR/ESP models. According to Krishnan and Patnam (2013), social learning (through neighbours) is a powerful force for adopting new technologies which may be far more persistent than learning from extension agents. Membership in farmer groups reflect the intensity of contacts with other farmers (Adegbola and Gardebroek, 2007) and may also indicate exposure to information on the SWCT.

Table 3: Full information ESR/ESP results for the adoption of SWCT (first stage results)

Variable	Selection equation
Age	-0.002
	(0.006)
Sex	-0.380**
	(0.166)
Education	0.044*
	(0.025)
Farm size	-0.025
	(0.023)
Household size	0.108***
	(0.034)
Contacts	0.027***
	(0.006)
Credit	0.187
	(0.315)
Livestock	-0.003
	(0.028)
Off-farm	0.241
	(0.157)
Leadership	-0.240
	(0.171)
Labour	0.000
	(0.001)
Years	-0.005
	(0.005)
Improved variety	1.003***
	(0.190)
Slope	-0.008
	(0.390)
Soil fertility	0.080
	(0.174)
Rainfall index	-0.045
	(0.051)
Distance capita	-0.000
	(0.000)
Kongwa	0.773***
	(0.177)
Membership	0.874***
	(0.174)
Neighbour	0.472*

	(0.256)
Constant	-2.437***
	(0.455)
N	575

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors appear in parentheses

4.2 Impacts on household welfare

The estimates for the average treatment effects on the treated (ATT) from the ESR/ESP models, which show the effects of SWCT adoption on household welfare, are presented in Table 4. These results are different from the simple mean differences presented in Table 2. The added contribution of adopting SWCT towards per capita household income was estimated at Tsh 51,328. In other words, the income of adopters that can be attributed solely to the adoption of SWCT was 49% higher than that of non-adopters. The results also show that the adoption of SWCT significantly increased HDDS by 77% and reduced food insecurity by 13%. Adoption also increased the probability of consuming iron and vitamin A-rich foods by 12% and 23% respectively. Finally, the probability of being food secure is 27% higher, on average, for adopting households than for non-adopting households when we consider the subjective food security indicator. The impact estimates are largely consistent with studies on climate-smart agricultural practices and SWCT (Abdulai and Huffman, 2014; Kassie et al., 2008; Di Falco et al., 2011; Issahaku and Abdulai, 2019).

Table 4: Impact of adoption of SWCT on household income, HDDS, HFIAS and subjective food security

Outcome variables	Mean of outcome variables		ATT
	To adopt SWC	Not to adopt SWC	
Household income	156793.900	105465.400	51328.440***
			(9916.926)
HDDS	6.246	3.535	2.711***
			(0.098)
HFIAS	4.040	4.626	-0.586 **
			(0.207)
Iron			0.225***
			(0.020)
Vitamin A			0.119***
			(0.024)
Subjective food security			0.271***
			(0.0391)

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors appear in parentheses

4.3 Distributional impacts of the adoption of SWCT

Table 5 reports the estimated IVQTEs of the adoption of SWCT on the continuous indicators of household welfare for the 0.1–0.9 quantiles. The 0.1 quantile includes the households with the lowest welfare, while the 0.9 quantile includes the sample households with the highest household welfare. Unlike previous studies which report unconditional quantile treatment effects based on observed characteristics, results in Table 5 also account for unobserved characteristics to ascribe a causal interpretation to the results. Contrary to the results found by Issahaku and Abdulai (2019), our results generally show that even though adoption benefits the poor and wealthy households alike, the marginal impacts of adoption are larger for the households with the highest household welfare and smaller for the households with the lowest welfare levels. The results are however in agreement with those found by Manda et al. (2017) and Wossen et al. (2018b) for improved crop varieties in Zambia and Nigeria.

Considering household income, the adoption effects are positive and significantly different from zero across most of the distribution. The adoption of SWCT exerts a significant positive and increasing effect on household income as we move from the 0.3rd (Tsh 89,857.141) to the 0.8th (Tsh 476,190.453) quantile. We can infer from these results that the increase in income associated with the adoption of SWCT tends to grow as income increase. The distributional impacts of SWCT on HDDS are slightly different as the effects are only significant in the lower quantiles of the HDDS distribution, even though the effects also increase as we move from lower to larger quantiles. The results also reveal that the food insecurity reducing effects of adopting SWCT are only significant in the 8th and 9th quantiles as shown in column 3. This implies that adoption mainly benefits households at the highest welfare levels.

Table 5: Unconditional quantile treatment effects of the adoption of SWCT on income and food security

Quantile	(1)	(2)	(3)
	Household income	**HDDS**	**HFIAS**
0.1	47857.143	1.000	-3.000
	(46903.902)	(0.609)	(13.474)
0.2	64000.000	2.000***	-4.000
	(50438.592)	(0.623)	(9.163)
0.3	89857.141*	1.000	-6.000
	(50792.735)	(0.762)	(5.802)
0.4	85571.422	2.000**	-7.000
	(54725.501)	(0.854)	(5.872)
0.5	137642.859**	1.000	-9.000
	(61525.485)	(1.041)	(7.025)

0.6	210416.656**	2.000*	-8.000**
	(92247.781)	(1.174)	(3.866)
0.7	294142.859**	1.000	-8.000**
	(147449.368)	(1.525)	(3.502)
0.8	476190.453**	1.000	-7.000
	(207054.190)	(1.676)	(4.444)
0.9	369750.000	1.000	-2.000
	(490032.387)	(1.663)	(3.675)

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors appear in parentheses

The IVQTEs results may be sensitive to the assumptions that come with the identification of the model, hence we also estimated the distributional effects of SWCT using the SD method based on observed factors.Second, unlike the IVQTEs results, we also estimated the effects for binary outcome variables (consumption of iron and vitamin A rich foods and food security). Following the approach described in section 3.2, the difference in the non-parametric regression line between the adopters and non-adopters at different levels of the propensity score is depicted in figure 2. The *x*-axes indicate estimated propensity for the adoption of SWCT, and the *y*-axes show the matched differences between adopters and non-adopters. The results generally show a steady and increasing income, HDDS, consumption of iron and vitamin A rich foods and subjective food security response to different levels of the estimated propensity scores, suggesting that farmers with a higher propensity to adopt, benefit the most from the adoption of SWCT. We observe a similar trend with the HFIAS curve, which shows a negative slope, indicating a reduction in food insecurity as the propensity to adopt increases. Results in figure 2 suggest that farmers self-select into adoption based on their comparative advantage (positive selection), consistent with Suri (2011). The smoothing-differencing results are there largely consistent with and lend credence to the ESR/ESP and IVQTEs results presented above.

Figure 2: Smoothing-differencing heterogeneous SWCT adoption effects on income, HDDS, HFIAS, Iron, Vitamin A and subjective food security

Note: Solid lines show the average treatment effect (local polynomial fit); dashed lines pertain to 95% confidence interval

4. Summary and Conclusions

The central region of Tanzania is predisposed to frequent droughts and significant erosion of the topsoils which has negatively affected the productivity of many crops in the country. Previous studies show that the adoption of soil and water conservation technologies (SWCT) is a potential solution to some of these problems by reducing drought and soil erosion risks, and; increasing crop yields and incomes. Nevertheless, in most of these studies, much attention has been given to the assessment of the impact of the adoption of SWCT on crop yields and net farm returns, with a few of them analysing the effect on household income and food security/nutrition. Moreover, empirical evidence on the distributional effects of the adoption of SWC technologies is still thin. This paper contributes to the empirical literature in this area by examining the average and distributional impacts of the adoption of SWCT on household incomes and food security (HDDS, HFIAS and subjective food security) and micronutrient consumption in central Tanzania. We use the endogenous switching probit (ESP), endogenous switching regression (ESR) and the instrumental variable unconditional quantile treatment effects (IVQTE) models, coupled with a recent household survey data from a sample of over 500 households to achieve our objective.

Consistent with previous adoption studies, our results indicate that the main factors influencing the adoption of SWCT are sex and education of the household head, household size, contacts with extension agents, farmers' group membership and neighbours' adoption decisions. Regarding the impact of adoption on household welfare, the results show that the adoption of SWCT significantly increases household income and food security. This underscores the importance of adopting SWCT in mitigating the adverse effects of climate change such as frequent droughts and soil erosion, common in the semi-arid regions of central Tanzania.

The IVQTEs complimented with the SD heterogenous results offer a more nuanced description of the relative effects of adopting SWCT over the entire household welfare distribution. Unlike the average treatment effects from the ESR/ESP models, the quantile treatment effects mainly show that the marginal impacts of adoption are larger for the households at the highest household welfare and smaller for the households at the lowest welfare levels, indicating that the effects are not uniform but heterogeneous.

The significance of contacts with extension agents and social networks (membership in a farmers' organization and neighbours' adoption decisions) implies that exposure to information on SWC technologies is essential to increase the adoption of these technologies. The results, therefore, suggest the need for policies and strategies which promote farmer organizations and effective extension services for greater adoption of soil enhancing and water harvesting technologies. Similarly, policies which centre on a farmer and his/her neighbours or farmer to farmer extension can go a long way in increasing the adoption and diffusion of SWCT. Interventions which centre on promoting interactions among farm households such as self-help groups and farmer field-days can increase the effectiveness of social networks in promoting the adoption of agricultural technologies (Mumin and Abdulai, 2021).

Finally, even though the link between the adoption of SWCT and crop productivity is well established in the literature, very few studies have quantified the impact of these technologies on labour outcomes. Although the results of this study have shown that labour is an important determinant of adoption, further research that explicitly examines the labour (family and hired) implications of the adoption of SWCT is important to design and develop technologies that are suitable for resource-poor farmers in developing countries.

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