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Impact of Soil and Water Conservation Practices on Household Vulnerability to Food Insecurity in Eastern Ethiopia: Endogenous Switching Regression and Propensity Score Matching Approach

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Abstract

Governmental and developmental partners invest substantial resources to reduce land and water degradation in order to upgrade agricultural productivity, thus reducing food insecurity and related vulnerability in Sub-Saharan Africa. Understanding the impact of soil and water conservation on food insecurity outcomes would be a significant step toward improving environmental conditions, while ensuring sustainable and increased agricultural production. Therefore, this article analyzes the impact of adopting soil and water conservation on food insecurity and related vulnerability outcomes of farming households. A multi-stage stratified sampling procedure is used to identify a sample of 408 households from three districts in eastern Ethiopia. Vulnerability as expected poverty (three-step Feasible General Least Squares) is employed to analyze the vulnerability of sample households in the context of food insecurity. In addition, endogenous switching regressions with propensity score matching methods are combined to obtain consistent impact estimates. The study reveals that education and sex of household head, use of irrigation and fertilizer, source of information, and cultivated land are the main factors influencing the adoption of soil and water conservation. Moreover, adoption of soil and water conservation not only positively impacts the per capita food consumption expenditure and net crop value, it also significantly reduces the probability of farmers being food insecure, vulnerable to food insecurity, as well as transient and chronically food insecure. Therefore, policymakers and development organizations should consider soil and water conservation as a main strategy to reduce land degradation and improve the livelihoods of the rural farm households.

Keywords: Soil and water conservation; Impact; Endogenous switching regression; Vulnerability to food insecurity; Ethiopia

1. Introduction

Ethiopia is one of the fastest growing countries in sub-Saharan Africa, with double digit economic growth in most years since 2005. Between 2000 and 2015, the poverty rate fell from 44 to 30 percent of the population (IFPRI 2015). However, the figure remains high and Ethiopia ranks 174 out of 188 countries on the 2015 UN Human Development Index and 104 out of 119 in the Global Hunger Index ratings (IFPRI 2017). IFPRI (2015) also reports that a large portion of the population, about 40 percent, consumes less than the recommended daily calories. Although agricultural growth is an important factor behind the reductions in poverty and food insecurity, with 72 percent of its active population employed, the prevalence of poverty and food insecurity remains very high in rural Ethiopia (World Bank 2016).

Food insecurity and poverty in Ethiopia is a long-term phenomenon caused by a combination of both natural and man-made factors; for example, inadequate alternatives to nonfarm income, unreliable rainfall patterns, land degradation, poor infrastructure, poor access to modern agricultural inputs, and limited credit facilities (Dercon and Christiaensen 2011; Dercon and Krishnan 1998; Wisner et al. 2004;Wisner et al. 2004). Land and water degradation significantly affects household poverty, food insecurity, and related vulnerability. Empirical evidence shows that aggregate impacts of land and water degradation on food security are negative (see Berry et al. 2003; Demel 2001; Paulos 2001; Shibru and Kfle, 1998; Demel 2001; Shibru 2010).

Kirui and Mirzabaev (2015) report that over 25 percent of the land in Ethiopia is degraded at moderate to very severe levels. However, according to Borrelli et al. (2017), 0.084 million km², or 9.5 percent of the country, is among the most intensively eroded regions in the world. It is more severe in the Ethiopian highland, where 85 percent of Ethiopian residents live, along with 77 percent of livestock population, and where there is intensive agriculture (Bewket, 2007). Paulos (2001) and Berry et al. (2003) state that, related with land degradation and unsustainable land management, every year Ethiopia loses billions of Birr.[1] Accordingly, Ethiopia loses at least three percent of agriculture Gross Domestic Product (GDP); equivalent to US$ 162 million in 2007 agricultural GDP (Gebreselassie et al. 2016). Moreover, land and water degradation reduces agricultural productivity, thus contributing immensely to food insecurity and poverty (Shibru 2010). Accordingly, the amount of grain lost due to land degradation could feed more than 4 million people annually (Demel 2001).

Due to extensive land degradation, the natural resource base is deteriorating over time, directly resulting in food insecurity and related vulnerability (Barrett et al. 2002; Berhanu et al. 2010; Pender and Gebremedhin 2006). For instance, land and water degradation could affect all dimensions of food security in complex ways (food availability, accessibility, sustainability, and utilization). Land and water degradation has reduced agricultural production and productivity, while also affecting dietary diversity due to changes in the suitability of land for crop production (Pimentel and Burgess 2013; Sonneveld 2002; Demel 2001). This may directly affect household income and food availability. Lower yields could increase the prices of major

[1] *Birr is Ethiopia currency (1USD=23.32 Birr).*

crops due to reduce market supply at local and national levels (Slaymaker 2002). Under such circumstances, subsistence farmers, who already have high food expenditures, would have to sacrifice further to meet their adequate nutritional requirements and, in addition, be unable to escape food insecurity in the near future (Stocking 2003).

However, the sustainable use of natural resources at household and community levels may improve the welfare of farming households and help them to escape from the food insecurity and venerability trap. Various studies (Hishe et al. 2017; Amare et al. 2014; Tenge et al. 2011; Keesstra et al. 2018) indicate that Soil and Water Conservation (SWC) helps the reduced rainfall be transformed into runoff that increases soil fertility and moisture content, also improving soil health and function that maintains and restores the eco-system. In addition, in the long run SWC will improve ecology and environment as well as local climate which is directly and indirectly associated with sustainable agriculture. Thus, adopting SWC could substantially impact not just crop production, but also the household income of small holder farmers. According to Bogale and Shimelis (2009), and Mozumdar (2012), high production and household income increases the farmers' purchasing power and consumption from own production. Moreover, as argued by Jenkins et al. (2003), Finnie and Sweetman (2003), and Devicienti (2002), households with high income are less likely to be food insecure and less vulnerable to external shocks.

The Ethiopian government has considerable investments in conserving the environment, with its main objective being the improvement of livelihood opportunities through improved environmental conditions that ensures sustainable and increased agricultural production. During the 1980s, the country started SWC campaigns, encouraging the implementation of SWC practices in drought prone and extremely land degraded parts of Ethiopia (Mekuriaw and Hurni 2015). However, as farmers were forced to implement a conservation structure designed by experts, the program was not effective (Haregeweyn et al. 2015; Mekuriaw et al. 2018; Mekuriaw and Hurni 2015; Wolka 2014). Since the Ethiopian People Republic Democratic Front (EPRDF) came to power in 1991, SWC has been a part of the agriculture extension package.

Since the beginning of the 2000s, under the SDPRP[2] framework launched in 2002 and the PASDEP launched in 2005, participatory watershed management is recognized by the government. Given this strategy, different sustainable land management programs have been implemented throughout the country. Further, the country developed a national guideline known as Community Based Participatory Watershed Development Program (CBPWDP) in 2005 (MoARD 2005). Additionally, the integrated SWC implements different conservation technologies (such as Bench terracing, Soil bund, Stone bund, farm forestry, and so on) in selected areas. The main goal of this approach is to improve the living standards and welfare of the most vulnerable rural households and communities through SWC practices on individual

2 "Two successive Poverty Reduction Strategic Papers (PRSP), i.e., the Sustainable Development and Poverty Reduction Program (SDPRP) launched in 2002 and the Plan for Accelerated and Sustained Development to End Poverty (PASDEP) were instituted in 2005. The two broad strategies of PASDEP is to reduce poverty by stimulating rural growth through agriculture and rural development, and to strengthen public institutions to deliver services" (Gelaw and Sileshi 2013).

farm plots and communal land, rainwater harvesting, promoting sustainable agricultural practices, and income diversifying agricultural practices (Gebregziabher et al. 2016). In addition, the program also promotes and gives training to farmers on how to integrate SWC with livestock fattening, improved poultry and apiculture production, and fruit tree promotion.

Despite these efforts to improve livelihood opportunities, as well as increase farm productivity through improved environmental conditions, the impacts of conservation practices on food consumption expenditure, food insecurity, and related vulnerability outcomes are not yet systematically analyzed. Various studies examine the impact of SWC on technical efficiency, crop production, and crop income. A study on the impact of SWC in Ethiopia shows that SWC in Ethiopia has very low returns, with most smallholder farmers not receiving adequate incentive from their initial investment (Kassie and Holden, 2006). In addition, Nyangena and Köhlin (2009), also reveal that plots using SWC measure generate less yield values per hectare than without conservation. In contrast, Adgo et al. (2013), studying the impact of SWC in Ethiopia, find that adoption can significantly increase *teff*, barley, and maize productivity. Likewise, Zikhali (2008), also find that soil conservation technology enhanced productivity in Zimbabwe. In addition, Bekele (2003) and Yenealem et al. (2013) find that plots with soil and water conservation activities significantly increase crop production compared to those without. Furthermore, Tesfaye et al. (2016) also confirms that SWC practices in Ethiopia increase grain productivity, thus benefiting farm communities.

However, existing studies focus on current production and household crop income (e.g., Adgo et al. 2013; Bekele 2003; Yenealem et al. 2013; Zikhali 2008), failing to address the effect of conservation measures on current and expected welfare effects (food insecurity and related vulnerability) as well as other food security categories (transient and chronic food insecurity). Thus, to the best of our knowledge, this is the first rigorous paper examining the association between food insecurity and related vulnerability with adoption of SWC in Africa, in general, and Ethiopia, in particular. Impact assessment provides major input for policy makers and planners when designing and developing effective and sustainable conservation strategies to mitigate current and future food insecurity through increased farm productivity. Furthermore, this study employs standard Per Capita Food Consumption Expenditure (PCFCE) and the Vulnerability as Expected Poverty (VEP) approach to measure food security and Vulnerability to Food Insecurity (VFI) of farming households, respectively. This allows us to check the impact of adoption on current food insecurity as well as expected food insecurity consumption after taking idiosyncratic shocks into account. Thus, the empirical premise of this article is to analyze the direction and magnitude of SWC effects on PCFCE, net crop value, food insecurity, and VFI in eastern Ethiopia. Moreover, the paper focuses on further disaggregated food security status categories among adopters and non-adopters, assessing the relationship between SWC adoption and food insecurity along with related vulnerability outcome variables by controlling for the effects of confounding factors.

The article is structured in five sections including the preceded introduction. The second section contains data collection and description of the study area; followed in the third section by the empirical methods describing an endogenous switching regression (ESR), propensity score matching (PSM), and VFI assessment. The fourth section discusses the results. Finally, the fifth section provides conclusions and implications for policy.

2. Data collection and description of the study area

2.1. Sampling procedure and data collection

The study was conducted in East Hararghe, Ethiopia, in August and September, 2017. A multi-stage sampling technique was employed to select districts, *kebeles,*[3] and sample households. In the first stage, from the program intervention area, three districts (Deder, Gurugutu and Haramaya) were selected randomly. In the second stage, three *kebeles* were selected purposively from each district based on the extent of soil degradation problems and program implementation. Thereafter, the villages were stratified into two strata (treated and controlled villages). However, the two strata comprised the same social, infrastructural, agro-climatic, and economic characteristics. Finally, 208 households that did not adopt any SWC measures from control villages where no SWC interventions were made and 200 households that did adopt at least one SWC measures from treated villages with SWC interventions were randomly selected using proportionate probability sampling based on the size of each district and *kebele*.

Table 1. Sample districts, *Kebeles* and number of sample households

Districts	*Kebeles*	Adopters Sample	Non- Adopters Sample	Total sample
Deder	Chafe Gurumu	28	27	55
	Gaba Gudina	34	30	64
	Walfaa Gabon	21	17	38
Gurugutu	Biftu Dirama	15	17	32
	Ifa Jalala	29	25	54
	Mauhasa Walfaa	16	22	38
Haramaya	Biftu Geda	17	24	41
	Amuma	15	20	35
	Ifa Oromiya	25	26	51
	Total	200	208	408

For the household survey, a structured questionnaire was designed and pretested before implementation. The survey covered a wide range of issues that influence SWC technology adoption, as well as food security and related vulnerability at household levels. The survey collected information on each households' socio-economic and institutional characteristics, soil and water conservation, different shocks and coping strategies, as well as the available relevant food security programs and activities. Furthermore, the types and amount of food consumed by each household from different sources was collected. This 'food basket' was valued at local prices to determined PCFCE of the households and food poverty line.

3 Kebele is usually a named peasant association and is the lowest administrative unit in the country.

2.2. Description of the study area

This study was undertaken in eastern Ethiopia, specifically in East Hararge, a zone in the regional state of Oromia. East Hararghe is located between 7°32'- 9°44' North latitudes and 41°10'- 43°16' East longitudes. East Hararghe is characterized by rugged, dissected mountains, deep valley, plateaus, and plains, which are categorized into plateau, lowland, and transitional slope with altitudes ranging from 500 to 3,405 meters above sea level (PEDO, 2012). The zone is characterized by three agro-ecological zones: semi-arid (62.2 percent), semi-temperate (26.4 percent), and temperate tropical highlands (11.4 percent). This wide range of agro-climatic zone allows the area to produce a variety of products, including cereal crops like sorghum, maize, wheat, and *teff*; vegetables like potatoes, onions, shallots, and cabbage; as well as perennial crops like coffee and *Khat* (*Catha adulis*). Livestock keeping is also an integral activity of farmers.

East Hararge is highly prone to regular droughts as well as serious land and other natural resources degradation. Thus, the central and regional governments, along with other development partners, promote different policies and programs to reverse this situation. For instance, with the framework of the federal government's CBPWDP, an integrated SWC program, has been implemented since 2006 in selected districts. The main goal of this program is to improve the livelihoods opportunities of rural communities and reduce food insecurity and poverty through integrated natural resource management (Gebregziabher et al. 2016).

3. Econometric modeling strategy

3.1. Endogenous Switching Regression (ESR)

When making an accurate impact assessment of SWC adoption on food insecurity and the VFI of farm households, the observable and unobservable characteristics of the adopters (treatment group) and non-adopters (control group) must be captured. However, most impact assessment approaches using non-experimental data (not randomly assigned) fail to capture observable and/or unobservable characteristics that affect adoption and outcome variables. For instance, instrumental variables capture only unobserved heterogeneity, but the assumption is that the parallel shift of outcome variables can be consider as a treatment effect (Ahmed et al. 2017; Kabunga et al. 2012; Shiferaw et al. 2014). In contrast, using regression models to analyze the impact of a given technology using pooled samples of users and non-users might be inappropriate because it gives the similar effect on both groups (Ahmed et al. 2017; Kassie et al., 2010; Kassie et al. 2011b). A methodological approach that overcomes the aforementioned limitations is endogenous switching regression (ESR), which is the most frequently used common method to analyze the impact of a given technology (Abdulai and Huffman 2014, 2014; Ahmed et al. 2017; Asfaw et al. 2012; Di Falco et al. 2011; Jaleta et al. 2018; Kabunga et al. 2012; Kassie et al. 2011a; Shiferaw et al. 2014). In this paper, we employ parametric ESR with non-parametric PSM technique to reduce the selection bias and assure consistent results by capturing both the observed and unobserved heterogeneity that influence the outcome variable as well as the adoption decision.

The impact of SWC technology on food insecurity and related vulnerability under the ESR framework follows two stages. The first stage, adoption of SWC is estimated using a binary probit model as selection, while in the second stage both linear regression and binary probit models are employed to assess the association between outcome variable and adoption of SWC (Jaleta et al. 2018; Shiferaw et al. 2014). The detail of the econometric modeling framework used is specified below.

The study adopts the expected utility maximization theory for farmer adoption of SWC measures. Individual i adopts SWC on their farm plot if expected utility from adoption (U_{swc}) is greater than the expected utility from non-adoption (U_{nswc}), i.e. U_{swc} -U_{nswc}>0.

$$I_i^* = \beta X_i + v_i \quad where\ I_i = \begin{cases} 1 & if\ I_i^* > 0 \\ 0 & otherwise \end{cases} \qquad (1)$$

Where I_i^* is the latent variable capturing the unobserved preferences associated with the adoption of SWC determined by observed farm and socio-economic characteristics of the household (X_i) and the error term (v_i). I_i is observed binary indicator variable that equals 1 if a farmer adopts SWC practices and zero otherwise, while β is a vector of parameters to be estimated.

In this article, adoption is defined if farmers used at least one of the introduced SWC technologies (soil bund, stone bund, and bench terracing) on one of their farm plots. However, according Jaleta et al. (2018), if selection equation (first stage) is endogenous in the outcome equation (second stage), result would be biased and inefficient. Therefore, it is vital to use instrumental variable methods to identify the second stage equation from the first stage equation. The instrumental variable should affect the adoption of SWC but not the outcome variables, such as PCFCE, net crop value, food insecurity, VFI, as well as chronically and transient food insecure. While we acknowledge that the selection of instrumental variables is empirically challenging, we use sources of information (government extension (yes=1) and farmers cooperatives (yes=1)) as a selection instrument. Adegbola (2007) indicates that the source of information is a vital element which influencing adoption of a given agricultural technologies through facilitate diffusion process by access a certain source of information. Shiferaw et al. (2014), Di Falco et al. (2011) and Khonje et al. (2015) use these variables as instruments to assess the impact of adopting improved seed and adaptation to climate change on household food security and welfare. Thus, these variables are more likely to be correlated with the adoption of SWC but not with the food insecurity and vulnerability outcome variables or correlated with the unobserved. Moreover, we also check the validity of the instrument variable using a falsification test. The test shows that the variable significantly affects the adoption decision but not our outcome variables.[4]

4 Instrument variable are jointly statistically significant in the selection equation [$\chi 2$ = 25.30 (p = 0.0000)] but not outcome functions: for example binary food insecurity status of adopter [$\chi 2$ = 1.11 (p = 0.5742)] and non-adopter; [$\chi 2$ = 1.04 (p = 0.5937)] as well as the PCFCE for adopters [F = 0.43 (p = 0.6520)] and non-adopters [F = 0.87 (p = 0.4188)]. We also find similar result for other outcome functions (crop income and binary chronic and transitory food insecurity, VFI).

The outcome regression equations both for adopters (regime 1) and non-adopters (regime 2) can be written as an endogenous switching regime model:

$$Regimes\ 1: Y_{1i} = \theta_1 Z_{1i} + \varepsilon_{1i,} \qquad if\ I = 1 \qquad (2a)$$
$$Regimes\ 2: Y_{2i} = \theta_2 Z_{2i} + \varepsilon_{2i,} \qquad if\ I = 0 \qquad (2b)$$

where Y_i represents outcome variables (PCFCE, net crop value and a binary outcome variables such as food insecurity, VFI, chronically and transient food insecure status) of smallholder farmer i for each regime (1 = adopter of SWC practices and 0 = non-adopter of SWC practices), Z_i is a vector of farm and socio-economic characteristics of household that affects outcome variables, and θ_i is a vector of parameters to be estimated. The error terms in Equations (2) and (3) are distributes to be trivariate normal, with mean zero and a non-singular covariance matrix:

$$cov(\varepsilon_1, \varepsilon_2, v) = \begin{pmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{1v} \\ \sigma_{21} & \sigma_2^2 & \sigma_{2v} \\ \sigma_{v1} & \sigma_{v2} & \sigma_v^2 \end{pmatrix}, \qquad (3)$$

where σ_1^2 , σ_2^2, and σ_v^2 are the variance of the outcome function of regimes 1 and 2, as well as the selection equation, respectively, σ_{12} , σ_{1v}, and σ_{2v} represent the covariance of ε_{1i}, ε_{2i}, and v_i. The variance of selection question (σ_v^2) is assumed to be equal to 1 since the coefficients (β) are estimable only up to a scale factor. Maddala (1983), confirm that the covariance of the error terms (ε_{1i} and ε_{2i}) is not defined since outcome variables ($Y_{1i}$and Y_{2i}) are not captured at the same time. The expected values of error term of the second stage are non-zero because the error term of the first stage (v_i) and second stage (ε_{1i} and ε_{2i}) are associated each other. The expected value of error terms of question (2a) and (2b) can be expressed as follows:

$$E\left(\varepsilon_{1i} \middle| Y_i = 1\right) = \sigma_{1v} \frac{\emptyset(\beta X_i)}{\Phi(\beta X_i)} = \sigma_{1v}\lambda_{1i} \qquad (4a)$$
$$E\left(\varepsilon_{2i} \middle| Y_i = 0\right) = \sigma_{2v} \frac{\emptyset(\beta X_i)}{1 - \Phi(\beta X_i)} = \sigma_{2v}\lambda_{2i} \qquad (4b)$$

where $\emptyset(.)$ is the standard normal probability density function, $\Phi(.)$ is the standard normal cumulative density function, while $\lambda_{1i} = \frac{\emptyset(\beta X_i)}{\Phi(\beta X_i)}$ and $\lambda_{1i} = \frac{\emptyset(\beta X_i)}{1-\Phi(\beta X_i)}$ are the inverse Mills ratios (IMR) estimated from the first stage question. Then the variable included in the second stage questions capture both absorbed and unabsorbed heterogeneity in estimation procedure ESR (Jaleta et al. 2018). To address the heteroskedasticity arising from the generated regressors, the standard errors in questions (2a) and (2b) are bootstrapped (Ahmed et al. 2017; Jaleta et al. 2018; Shiferaw et al. 2014)

Based on the above context, comparing real and counterfactual scenarios of expected values of the outcomes of adopters, the average treatment effect on the treated (ATT) is obtained. Similarly average treatment effect on the untreated (ATU) also can be calculated by comparing the expected values of the outcomes of non-adopter in real and counterfactual scenarios (Khonje et al. 2015). Following Abdulai and Huffman (2014); Asfaw et al. (2012); Jaleta et al.

(2018); Kabunga et al. (2012); Shiferaw et al. (2014), the expected values of the outcomes of both adopters and non-adopters in reality and the counterfactual are given as follows:

Adopters with adoption of SWC (real):

$$E\left[Y_{1i}\,\middle|X, I = 1,\right] = \theta_1 X_{1i} + \sigma_{1v}\lambda_{1i} \tag{5a}$$

Non-adopters without adoption of SWC (real):

$$E\left[Y_{2i}\,\middle|X, I = 0,\right] = \theta_2 X_{2i} + \sigma_{2v}\lambda_{2i} \tag{5b}$$

If adopted had non-adopted SWC (counterfactual):

$$E\left[Y_{2i}\,\middle|X, I = 1,\right] = \theta_2 X_{1i} + \sigma_{2v}\lambda_{1i} \tag{5c}$$

If non-adopted had adopted SWC (counterfactual):

$$E\left[Y_{1i}\,\middle|X, I = 0,\right] = \theta_1 X_{2i} + \sigma_{1v}\lambda_{2i} \tag{5d}$$

Hence, ATT of adopter is computed as the difference between (5a) and (5c):

$$\begin{aligned} ATT &= E\left[Y_{1i}\,\middle|X, I = 1,\right] - E\left[Y_{2i}\,\middle|X, I = 1,\right] \\ &= (\theta_1 - \theta_2)X_{1i} + (\sigma_{1v} - \sigma_{2v})\lambda_{1i} \end{aligned} \tag{6}$$

Likewise, ATU of non-adopters is computed as the difference between (5b) and (5d):

$$\begin{aligned} ATU &= E\left[Y_{1i}\,\middle|X, I = 0,\right] - E\left[Y_{2i}\,\middle|X, I = 0,\right] \\ &= (\theta_1 - \theta_2)X_{2i} + (\sigma_{1v} - \sigma_{2v})\lambda_{2i} \end{aligned} \tag{7}$$

According to Khonje et al. (2015), Shiferaw et al. (2014) and Ahmed et al. 2017, ESR models have a very strong exclusion restriction and the falsification test may not be adequate to confirm identification. Thus, results may be sensitive to selection of instrumental variables. Therefore, we also use binary PSM to further robustness check of the results obtains from ESR. PSM helps to adjust for initial differences between treated and control groups by constructing a statistical comparison group that is based on a model of the probability of treatment participation, using observed farm and socio-economic characteristics (Caliendo and Kopeinig 2008; Rosenbaum and Rubin 1983; Winters et al. 2011). Adopters are then matched on the basis of this probability (propensity score) to non-adopters (Rosenbaum and Rubin 1983). The ATT of the SWC can be obtained by comparing the mean outcomes between treatment and control groups (Imbens and Wooldridge 2008; Wooldridge 2002; World Bank 2010). This approach is widely applied in the literature (e.g., Amare et al. 2012; Dillon 2011; Kassie et al., 2010 Manda et al. 2018) and we do not present the detail methodology here. For a detailed specification and the steps of PSM, see Imbens and Wooldridge (2008), Wooldridge (2002), and World Bank (2010).

3.2. Vulnerability as expected poverty

We adopt an econometric model for analyzing household vulnerability to food insecurity proposed by Chaudhuri et al. (2002) and Christiaensen and Subbarao (2005). The model follows the VEP approach, using PCFCE as a measure of household welfare. Hence, this paper

uses the VEP approach, to the analysis of vulnerability of sample households in the context of food security.
The vulnerability of the household during at time t is expressed as the probability that the household faces of falling below the minimum food requirements at time t + 1:

$$V_{it} = P\ (\mathrm{c}_{\mathrm{it+1}} < z) \qquad (8)$$

Where the vulnerability of a household (V_{it}) during at time t, $C_{it+1,}$ is the household's PCFCE (welfare indicator) at time t + 1 and z is the threshold level (food poverty line).

The VEP approach, using expected mean and variance of household PCFCE, estimates household vulnerability in the context of food insecurity. According to Bogale (2012) and Günther and Harttgen (2009), the expected mean of PCFCE is determined by the household socio-economic, institutional, and farm characteristics as well as community characteristics, whereas the variance (also known as volatility) in household consumption captures the household and community shocks that influence to differences in PCFCE for households that share the same characteristics (Günther and Harttgen 2009). As proposed by Christiaensen and Subbarao (2005), the stochastic process generating the PCFCE of a farming household i can be expressed as follow:

$$\ln c_i = x_{\mathrm{i}}\beta + \varepsilon_{\mathrm{i}} \qquad (9)$$

Where C_i is log of PCFCE level, X_i is represents observable farm and household socio-economic characteristics, β is a vector of parameters, and ε_i is a disturbance term with mean zero and variance of $\sigma^2\, \varepsilon_i$ (heteroscedastic). This implies that variances of the error term vary across households depending on farm and household socio-economic characteristics. Then, the variance of the unexplained part of PCFCE ε_i regressed on household characteristics (X_i) to generate estimates for the expected variances specified as:

$$\sigma^2\, \varepsilon_i = x_{\mathrm{i}}\theta + \tau_{\mathrm{i}} \qquad (10)$$

Where θ represents the vector of parameters to be estimated and τ is the error term of equation 10.
However, due to heteroscedasticity, the estimated β and θ is inefficient but not biased. Hence, as Christiaensen and Subbarao (2005); Chaudhuri (2000), and Chaudhuri et al. (2002) suggest, we used Three Step Feasible Generalized Least Squares (FGLS) to obtain that to obtain efficient parameters ($\hat{\beta}$ and $\hat{\theta}$).

The steps involved include, first, an estimation procedure applying the Ordinary Least Squares (OLS) method to equation (9) and estimates the residual. Then equation (10) is estimated by OLS using the squared residuals from the estimation of equation (9) as dependent variables. The predictions from this regression are used to re-estimate equation (10) by OLS after having weighted each residual by $X_i\theta$. The new estimates of θ are asymptotically efficient and are used to weight equation (9), which is re-estimated using weighted least squares to obtain asymptotically efficient estimates of β (Bogale 2012). Finally, using the FGLS asymptotically efficient of β and θ, we estimate the expected and variance of log of PCFCE for each household as follows (Bogale 2012; Mutabazi et al. 2015).

$$\begin{aligned} E\,[\ln c_i/x_i] &= x_{i\hat{\beta}} \\ V\,[\ln c_i/x_i] &= x_{i\hat{\theta}} \end{aligned} \tag{11}$$

Assuming that household PCFCE is log-normally distributed, each household's probability of food insecurity at time t + 1 is expressed as:

$$\widehat{V} = \widehat{P}(\ln c_i < \ln z/x_i) = \emptyset\left(\frac{\ln z - \ln\widehat{c_i}}{\sqrt{\widehat{\sigma}_i^2}}\right) \tag{12}$$

Where $\emptyset$ is the cumulative density of the standard normal distribution; $\hat{\sigma}_i^2$ is variance of standard error of the regression; $\widehat{c_i}$ and Z are the expected household PCFCE and threshold level (food poverty line), respectively; and $\hat{v}$ is the probability each household faces of falling below the threshold level, with value ranging between zero and one. Chaudhuri et al. (2002), justify a threshold measure that is used to define vulnerable households as those with an estimated vulnerability coefficient above or equal to 0.5. Thus, we classify households as vulnerable if $\widehat{V}$ is above or equal to 0.5 and, otherwise, non-vulnerable.

Furthermore, to determine current household food insecurity status, we use the amount of money required to achieve the daily minimum dietary requirement. The government of Ethiopia set the minimum acceptable level of per capita calorie intake per day to 2200 (MoFED 2002). Thus, a household is considered to be food insecure if the amount of money it spends on food is not adequate to purchase a basic diet that is nutritionally adequate. Accordingly, the amount of money required to achieve the daily minimum dietary requirement (food poverty line) is Birr 2637.86 per annum. The CSA (2017) country and regional level consumer price indices report that the Consumer Price Index (CPI) of the survey area (Oromia regional state) was 171.4 percent (December 2011 = 100). Thus, the food poverty line is deflated in order to take into account the effect of inflation. Therefore, the adjusted food poverty line is Birr 1539 per adult equivalent, per year, at the end of 2011 constant price. Thus, a household is considered food insecure if PCFCE is less than food poverty line; otherwise food secure.

Combining vulnerability status with the current food insecurity status of household, we extend the analysis into several food insecurity and vulnerability categories among adopters and non-adopters. Accordingly, currently food secure and less vulnerable households are consider as stable food secure status; currently food insecure and high vulnerable households are consider as chronic food insecure; households are currently food secure and high vulnerable and vice versa are consider as transient food insecure.

4. Result and discussion

4.1 Descriptive analysis

Before embarking on the impact assessment, it is important to describe socio-economic, institutional, and farm characteristics among the adopter and non-adopter households (Table 2). Accordingly, about 91 and 83 percent of adopters and non-adopters, respectively, are male headed households. The average household head age of adopters and non-adopters is 39.94 and 40.43 years, respectively. However, a majority of family members are aged less than 15 or greater than 64 years, which means the dependency ratio is high (averaging 1.33 for adopters and 1.25 non-adopters). The average family size of adopters and non-adopters is 6.24 and 6.18, respectively. As far as the household head educational status is concerned, 40.69 percent of household heads never attended formal education. Further, the descriptive statistics reveal that farmers adopting SWC are more educated (on average 4.46 years) than non-adopters (on average 2.88 years).

Table 2 Description of explanatory variables among adopter and non-adopter

Characteristics	Description	Adopters N=200 Mean	SD	Non-Adopters N=208 Mean	SD	Total Sample N=408 Mean	SD
Age	Age of the head (in years)	39.940	12.545	40.428	12.940	40.189	12.735
Education	Level of education in numbers of years	4.460***	3.631	2.875	3.547	3.652	3.671
Family size	Household size (number)	6.240	1.998	6.178	2.074	6.208	2.035
Sex	Dummy of sex of head (1=male)	0.910***	0.287	0.827	0.379	0.868	0.339
Dependence ratio	Dependence ratio	133.445	96.725	125.194	96.275	129.239	96.466
Cultivated land	Total cultivated land holding	0.317***	0.188	0.263	0.155	0.289	0.174
Numbers of plot	Total numbers of plots own	1.995	0.848	1.889	0.806	1.941	0.827
Off-farm	Dummy for participation in off-farm (Yes=1)	0.440	0.498	0.476	0.501	0.458	0.499
Use of fertilizer	Dummy for using fertilizer (Yes=1)	0.595**	0.492	0.490	0.501	0.542	0.499
Livestock TLU	Livestock own (Tropical Livestock Unit)	1.939*	1.825	1.627	1.957	1.780	1.898
Information EA	Dummy for information from extension agent (Yes=1)	0.850***	0.357	0.659	0.475	0.752	0.432
Information FC	Dummy for information from farmers' cooperative (Yes=1)	0.215*	0.412	0.149	0.356	0.181	0.385
Dis. FTC	Average walking distance to FTC in minutes	29.425	27.962	27.197	22.995	28.289	25.544
Use of irrigation	Dummy for using irrigation (Yes=1)	0.375	0.485	0.322	0.468	0.348	0.477
Erosion problem	Dummy for erosion problem (Yes=1)	0.650*	0.478	0.558	0.499	0.603	0.490
Received credit	Dummy for receiving credit (Yes=1)	0.155	0.363	0.115	0.320	0.135	0.342

***, **, and * significant at the 1, 5, and 10 percent probability levels, respectively

Generally, adopters have more cultivated land and larger livestock holdings, expressed as Tropical Livestock Unit (TLU), than non-adopters. Moreover, nearly 65 percent of adopters and 56 percent of non-adopters state that their cultivated land is degraded. Both rely on rain-fed agriculture, with only 35 percent accessing irrigation and 54 percent using chemical fertilizer. Concerning institutional variables, about 14 percent of the respondents have credit from formal credit institutions. Furthermore, out of the total sample households, 75.20 and 18.10 percent of households have access to information from government extension agents and from farmers' cooperatives, respectively, with those adopting SWC having greater access to information than non-adopters from both sources.

4.2. Food insecurity and vulnerability to food insecurity

Table 9 in the appendix presents the three-step FGLS regression results showing explanatory variables that are used to estimate the expected PCFCE and its variance, as well as to show the relationship between explanatory variables with expected PCFCE and its variance. The model outcome reveals that household head age and family size, as expressed by adult equivalence, are found to negatively, and significantly, influence expected food consumption expenditure while, using improved seed, total cultivated land, SWC adoption, and receiving credit all positively, and significantly, influencing expected food consumption expenditures. Moreover, we estimate VFI based on expected PCFCE and its variance using equation 12. Thereafter, VFI status of the sample household was determined using the vulnerability score threshold level (0.5). Accordingly, 43 percent of sample households are vulnerable, while households adopting SWC practices are less vulnerable (31 percent) than those not adopting (54 percent). In line with above results, the PCFCE and expected PCFCE of adopters are higher than that of non-adopters.

In addition, net crop value and current food insecurity status of households among adopters and non-adopters are also presented in Table 3. The results indicate that the average net crop value was Birr 8661.74 per ha per year; significantly higher for SWC adopters than non-adopters. Lastly, the current food insecurity status shows farmers who adopted SWC are less food insecure than non-adopting farmers.

Table 3. Descriptive statistics of outcome variables among adopters and non-adopters

Outcome variables	Adopters N=200		Non- Adopters N=208		Total N=408	
	Mean	SD	Mean	SD	Mean	SD
PCFCE/annum	3453.32***	1405.13	3067.04	1552.51	3256.39	1492.86
Expected PCFCE /annum	3280.82***	684.85	2842.64	537.95	3057.43	651.62
VFI	0.31***	0.46	0.54	.49	0.43	0.49
Food insecurity	0.305***	0.4	0.42	0.49	0.36	0.48
Net crop value	10791.02***	6723.25	6614.36	5356.15	8661.74	6407.99

***, **, and * significant at the 1, 5, and 10 percent probability levels, respectively

Combining vulnerability status with the current food insecurity status of household, we classified food security status of adopters and non-adopters in to stable food secure, chronic food insecure, and transient food insecurity as shown in Table 4.

Table 4. Food security status among adopters and non-adopters

Categories of food insecurity	Adopters N=200		Non- Adopters N=208		χ^2-value	Total N=408	
	No.	Percent	No.	Percent		No	Percent
Stable food secure	115	57.500	71	34.135		186	45.588
Chronic food insecure	36	18.000	63	30.288	24.762***	99	24.265

Transient food insecurity	49	24.500	74	35.577		123	30.147

***, **, and * significant at the 1, 5, and 10 percent probability levels, respectively

The results reveal that 57.50 percent of adopters have stable food security status, but only 34.14 percent of non-adopters. These households are currently food secure and have a low probability of falling into food insecurity in the near future (less vulnerable to food insecure). In contrast, 18.00 percent of adopters and 30.29 percent of non-adopters are food insecure for an extended period of time and are considered as chronic food insecure. Furthermore, 24.50 percent of adopters and 45.58 percent of non-adopters frequently move into and out of the state of food insecurity (transient). The Chi-test result indicates that there is a systematic relationship between the household's food insecurity status and adoption of SWC at the 1 percent level of significant.

These descriptive statistics indicate that households adopting SWC are less prone to food insecurity and VFI status than non-adopters. However, at this level, it is difficult to conclude that adopting SWC reduces current and future food insecurity. Thus, an impact assessment is needed to determine if this decrease in food insecurity and VFI is due to SWC adoption, by controlling for the observed and unobserved heterogeneity that affect the adoption decision and outcome variables.

4.3. Endogenous switching regression estimation results

The first stage ESR binary probit estimation results are presented in Table 5. Our probit model fits the data reasonably well [Wald Chi-squared = 78.2, P = 0.000)]. The model results reveal that household, socio-economic, and institution factors significantly influence the SWC adoption decision. Our results indicate that access to fertilizer is positively and significantly associated with adopting SWC. Thus, farmers with access to fertilizer have a higher probability of adopting SWC. Soil and water conservation adoption is also positively correlated with better educated household heads. Household heads who attend formal education have better understand the advantage and challenge of adoption of SWC (Fentie et al. 2013; Asfaw and Neka, 2017). Similarly, male headed households are also more likely to adopt SWC than female headed household. The possible explanation is that male headed households have better access to information and the labor required to implement new technology than do female headed household (Mekuriaw et al. 2018; Bekele and Drake 2006).

Farmers with access to information from government extension agents and farmers' cooperatives are more likely to adopt conservation technology. This is because the provision of information helps farmers become aware of the problem of land degradation and its consequences, while also acquiring new knowledge regarding new technology measures (Chilot 2007; Bogale et al. 2007; Shimeles et al. 2011). Another factor significantly and positively associated with adopting SWC is cultivated land. Farmers operating on larger amounts of cultivated land can allocate a small proportion of land for SWC structure than those with a small amount of cultivated land. Moreover, large cultivated land is linked with greater wealth and increased availability of capital, which directly affects SWC adoption (Paulos et al. 2001).

Table 5. Decision of adopting SWC: Probit model

Number of observations	408.000		
Wald chi2(15)	56.58		
Prob > chi2	0.000		
Pseudo R2	0.108		
Log pseudo likelihood	-252.139		
Variables	Coef.	Robust Std. Err.	Marginal Effects
Sex	0.335*	0.203	0.131
Age	0.007	0.006	0.003
Education	0.067***	0.023	0.027
Family size	-0.043	0.036	-0.017
DPR	0.001	0.001	0.000
Use fertilizer	0.252*	0.146	0.100
Distance FTC	0.002	0.003	0.001
Numbers of plot	-0.010	0.089	-0.004
Use of irrigation	0.149	0.150	0.060
Cultivated land	0.938**	0.462	0.374
TLU	-0.029	0.042	-0.011
Received credit	0.112	0.204	0.045
Information EA	0.685***	0.163	0.262
Information FC	0.437**	0.222	0.172
Off-farm	0.034	0.142	0.013
Erosion problem	0.209	0.143	0.083
_cons	-1.902***	0.438	

***, **, and * significant at the 1, 5, and 10 percent probability levels, respectively

The ESR model-based ATT and ATU of SWC adoption on outcome variables are presented in Table 6. As discussed earlier, the main outcome variables considered in this analysis are PCFCE and net crop value in Birr, as well as binary outcomes like food insecurity, VFI, chronic food insecurity, and transient food insecurity.

ESR impact results reveal that SWC adoption reduces the probability of current food insecurity, VFI, transient food insecurity, and chronically food insecurity. On the other hand, it increases PCFCE and net crop value. For those farmers who have adopted SWC but theoretically would have non-adopted, then their PCFCE decreases by Birr 205.97 ($8.83). This means, for an average family size expressed as adult equivalent of 4.89 per household, the ATT of food consumption expenditure at household level would decrease by Birr 1007.19 ($42.19) as a result of not adopting SWC. Similarly, if non-adopters would have adopted SWC, then their average PCFCE would have significantly increased by Birr 297.084 ($12.74) and at household level by Birr 1477.02 ($62.30). If SWC adopters had they not adopted, the average probability that they will food insecure increases by 10.50 percent. Likewise, if SWC non-adopters had adopted, the average probability of food insecurity decreases by 12.10 percent. On the other hand, households who actually adopted switching to non-adopted, then the probability of VFI status would have increased 14.10 percent but deceased 23.30 percent for non-adopters had they adopted SWC. Moreover, adoption of SWC reduces the probability of chronic food insecurity by 6.80 percent for adopters and 15.60 percent for non-adopters. Likewise, the average probability of transient food insecurity status (shift from food secure to food insecure and vice-versa) of adopters increases by 17.80 percent, if they had not adopted SWC, while if non-adopters had they adopted SWC, then transient food insecurity decreases a significant 7.50 percent.

In addition to food insecurity and vulnerability outcome variables, we also check impact of SWC on net crop value. The results indicate that the average net crop value of adopters falls by 3284.088 ($140.83) per ha if adopters not adopted. In the same way, if non-adopters had adopted, their average crop income would have increase by Birr 2980.135 ($ 127.79) per ha. Therefore, ESR reveals that the adoption of SWC in Ethiopia not only reduced food insecurity and related vulnerability but also increased food consumption expenditure by increasing net crop value.

Due to space limitations, the second stage of ESR, the estimated coefficients of PCFCE, and binary food insecurity and VFI are only presented in Table 10 of the appendix.

Table 6. Endogenous switching regression model result (average treatment effects)

Outcome variables	Farm household type and treatment effect	Decision stage		Treatment effect
		To adopt	Not to adopt	
PCFCE	ATT	3451.763	3245.793	205.970**
	ATU	3365.626	3068.542	297.084***
Food security	ATT	0.295	0.400	-0.105***
	ATU	0.299	0.420	-0.121***
VFI	ATT	0.312	0.452	-0.141***
	ATU	0.306	0.539	-0.233***
Transient food insecurity	ATT	0.244	0.422	0.178***
	ATU	0.281	0.356	0.075***
Chronic food insecure	ATT	0.175	0.243	-0.068**
	ATU	0.137	0.293	-0.156***
Net crop value	ATT	10791.02	7506.935	3284.088***
	ATU	9594.495	6614.361	2980.135***

***, **, and * significant at the 1, 5, and 10 percent probability levels, respectively

4.4. Binary propensity score matching estimation results

In addition to the ESR model, this study uses the PSM technique to check the robustness of the results obtained from the ESR model. Propensity scores (the probability of adoption in SWC) are estimated using a probit model. Figure 1 shows the distribution of adopter and non-adopter households with respect to estimated propensity scores. The figure illustrates the estimated propensity distribution for treatment and control households. The upper half of the graph refers to the propensity score distribution of treatment groups, while the bottom half shows the control groups. The y-axis refers to the densities of estimated propensity scores.

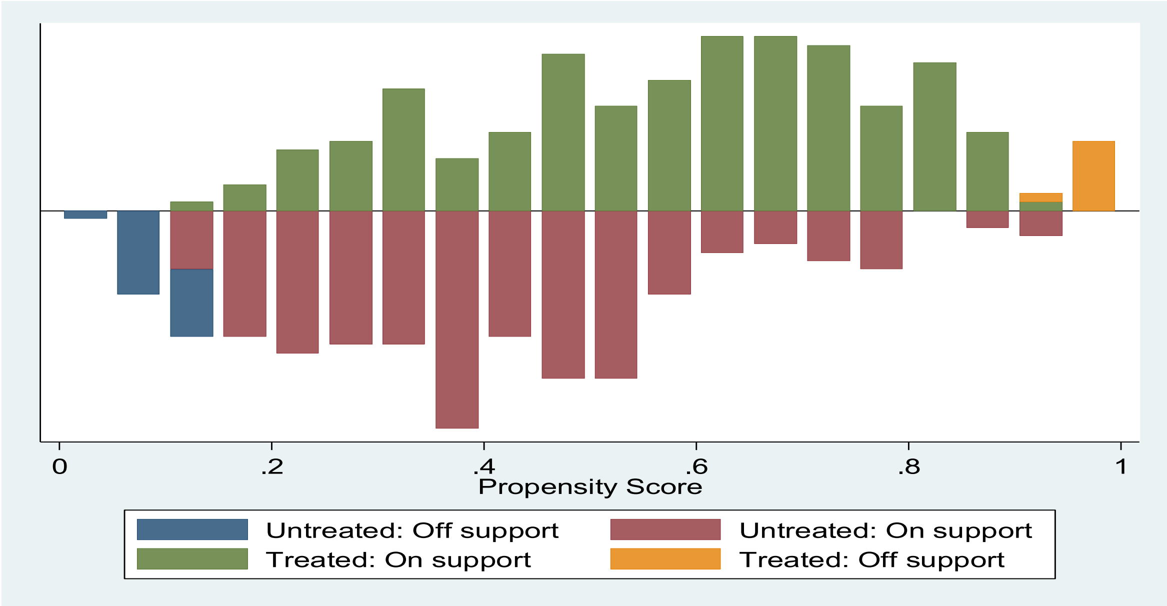

Figure 1. Distribution of estimated propensity distribution for treatment and control groups and common support area

A common support condition should be imposed on the propensity score distributions of households with and without adoption of SWC. The estimated propensity scores vary between 0.1437482 and 0.9463331 (mean = 0.5600339) and 0.0344507 and 0.8960822 (mean = 0.4203612) for the treatment and control groups, respectively. The common support region would then lie between 0.1437482 and 0.8960822. Accordingly, off support sample were discarded from the analysis in estimating the ATT in both groups. Thus, about 90 percent of adopters and non-adopters are in the common support area, showing substantial overlap between the two groups. Table 7 presents the balancing tests of each matching algorithm before and after matching. The results show that the mean standardized bias is reduced after matching (4.2 to 5.8 percent) compared to before matching (22.2 percent). Similarly, the Pseudo-R^2 reduces highly, from 10.82 percent to a range of 0.8 to 1.7 percent. The likelihood ratio tests (p-values) indicate the joint significance of all covariates at less than 1 percent probability level before matching, while it is insignificant after matching. Furthermore, the total bias significantly reduces in the range of 47.49 to 70.01 through matching. Thus, these tests clearly show that the matching process balances the observed characteristics between treated and control groups after matching.

Table 7. Covariates balancing tests before and after matching.

Matching algorithm	Pseudo-R^2		LR χ^2 (p-value)		Mean standardized bias		Total % |bias| reduction
	Before	After	Before	After	Before	After	
NNM[a]	0.1082	0.008	61.17 (0.000)	4.63 (0.997)	22.2	4.2	70.01
KBM[b]	0.1082	0.017	61.17 (0.000)	8.93 (0.916)	22.2	5.8	47.49
KBM[c]	0.1082	0.010	61.17 (0.000)	5.67 (0.991)	22.2	5.4	49.87

RCM[e]	0.1082	0.014	61.17 (0.000)	7.32 (0.967)	22.2	5.8	47.73
RCM[f]	0.1082	0.009	61.17 (0.000)	4.63 (0.997)	22.2	4.8	54.38

NNM[a] = One nearest neighbor matching and common support
KBM[b] = Kernel with band width 0.01 and common support
KBM[c] = Kernel with band width 0.025 and common support
RCM[e] = Radius Caliper 0.01 matching
RCM[f] = Radius Caliper 0.025 matching

Table 8 reports the ATT, based on PSM technique, using three different matching algorithm techniques (nearest neighbor matching (NNM), Kernel based matching (KBM), and Radius matching methods). The result reveals that, as in the ESR analysis, SWC adoption results in a statistically significant increase in both PCFCE and net crop value, while reducing the probability of food insecurity, VFI, transient food insecurity, and chronic food insecurity. The PSM result reveals that, on average, adoption of SWC boosts households' PCFCE in the range of Birr 232.683 to 352.276 (7.21 to11.51 percent). Similarly, it reduces the probability of food insecurity and VFI in the range of 9.10 to 11.50 percent and 12.90 to 16.60 percent, respectively. The probability of chronic (transient) food insecurity falls in the range of 7.10 to 7.50 percent (16.6 to 18.60 percent), respectively. Moreover, the result reveals that adoption of SWC significantly increase the annual net crop value, ranging from Birr 3127.105 to 3907.255 per ha. Therefore, apart from slight magnitude different between the PSM and ESR estimates, SWC adoption positively impacts PCFCE and net crop value, while reducing food insecurity and VFI. This may be because the PSM method does not consider unobserved heterogeneity between treatment and control groups. In line with this finding, Bekele (2003); Benin (2006); Kassie and Holden (2006); Pender and Gebremedhin (2006); and Kassie et al. (2009), all conclude that investing in SWC measures has positive impacts in terms of mitigating land degradation, while also improving crop production and income, especially in moisture deficit areas.

Table 8 Average treatment effects: propensity score matching. Features

Outcome variables	Matching algorithm	Mean of outcome variables based on matched observations		ATT	SE
		Adopters	Non-adopters		
PCFCE	NNM[a]	3457.124	3224.441	232.683*	135.682
	KBM[b]	3412.933	3066.386	346.546*	206.996
	KBM[c]	3454.214	3115.266	338.948*	185.058
	RCM[e]	3412.933	3060.657	352.276*	200.755
	RCM[f]	3454.214	3135.852	318.362*	181.284

Food insecurity	NNMa	0.291	0.383	-0.091*	0.054
	KBMb	0.307	0.418	-0.111*	0.064
	KBMc	0.296	0.410	-0.115**	0.058
	RCMe	0.307	0.413	-0.106*	0.062
	RCMf	0.296	0.409	-0.113**	0.057
VFI	NNM[a]	0.307	0.463	-0.157***	0.055
	KBM[b]	0.312	0.441	-0.129**	0.065
	KBM[c]	0.311	0.448	-0.137**	0.059
	RCM[e]	0.307	0.472	-0.166***	0.054
	RCM[f]	0.311	0.444	-0.133**	0.058
Chronic food insecure	NNM[a]	0.176	0.218	-0.042	0.038
	KBM[b]	0.178	0.215	-0.037	0.042
	KBM[d]	0.179	0.250	-0.071*	0.041
	RCM[e]	0.178	0.221	-0.043	0.041
	RCM[f]	0.179	0.253	-0.075*	0.045
Transient food insecurity	NNM[a]	0.246	0.412	-0.166***	0.053
	KBM[b]	0.254	0.440	-0.186***	0.060
	KBM[c]	0.250	0.426	-0.176***	0.056
	RCM[e]	0.254	0.435	-0.181***	0.059
	RCM[f]	0.250	0.421	-0.171***	0.056
Net crop value	NNM[a]	10776.351	7649.246	3127.105***	677.304
	KBM[b]	10613.861	6706.606	3907.255***	732.947
	KBM[c]	10628.070	7134.457	3493.613***	712.120
	RCM[e]	10613.861	6838.140	3775.721***	724.140
	RCM[f]	10628.070	7266.212	3361.858***	704.070

***, **, and * significant at the 1, 5, and 10 percent probability levels, respectively

5. Conclusions and implications for policy

This article analyzes the impact of SWC on food insecurity and vulnerability to food insecurity using primary data collected in eastern Ethiopia. We employ both parametric (ESR) and non-parametric (PSM) methods to reduce the effect of self-selection bias due to both observable and unobservable farm, household socio-economic characteristics as well as to test the consistence of the results, respectively.

The first stage ESR indicates that access to irrigation and fertilizer, household head education, household sex, sources of information, and cultivated land are significantly association with SWC adoption. The results obtained from both the ESR and PSM models are consistent, indicating that SWC adoption not only generates a significant positive impact on PCFCE and net crop value, but it also reduces food insecurity and VFI. In fact, the probability of food insecurity and VFI decreases by 10.5 and 14.1 percent, respectively, compared to their counterfactuals. Further, PCFCE and net crop value increase by Birr 205.97 and 3284.088 per ha due to SWC adoption, respectively.

Therefore, it can be concluded that SWC practices significantly contribute to the economic and social development of smallholder farmers by improving average PCFCE and net crop value as well as by reducing food insecurity and VFI. In addition, in countries like Ethiopia, where 40 percent of people suffer from food insecurity and land degradation is most severe, SWC practices should be considered as a principle strategy for improving the livelihoods of the rural farm households as well as for preventing land and water degradation. The findings of the study stress that policymakers and development organizations need to focus on better strengthening human and institutional capacity through enhanced education and continuous training on the effects of land degradation, as well as appropriate SWC, the use of fertilizer, and rainwater harvesting, in order to increase productivity and the adoption of SWC, thus restoring soil and agro-ecosystem health. Furthermore, governmental and developmental partners should give more attention on integrated SWC program not just improved environmental conditions and increase agricultural productivity but also improve the food security status of farming households as well as reduce vulnerability to external shock.

Table 9. Three-step Feasible Generalized Least Squares result for determinant of vulnerability to food insecurity (N=408)

Variables	Log food consumption expenditure			Variance of food consumption expenditure		
	Coef.	Robust Std. Err.	t	Coef.	Robust Std. Err.	t
Sex	-0.017	0.065	-0.26	-0.073	0.042	-1.75*
Age	-0.003	0.002	-1.75*	0.001	0.001	0.72
Education	-0.001	0.005	-0.16	-0.001	0.002	-0.25
Adult equivalent	-0.107	0.014	-7.65***	0.002	0.006	0.29
Dependence ratio	1.93E-04	1.82E-04	1.06	1.98E-05	8.57E-05	0.23
Annual income	1.94E-07	2.20E-06	0.09	1.06E-08	9.14E-07	0.01
Off-farm Activity	-0.003	0.039	-0.08	-0.002	0.019	-0.1
Use of fertilizer	0.005	0.045	0.1	-0.004	0.018	-0.23
Use of improved seed	0.129	0.045	2.89***	0.026	0.020	1.28
Use of irrigation	0.057	0.037	1.53	-0.025	0.018	-1.39
Cultivated land	0.243	0.134	1.81*	-0.012	0.071	-0.17
Adoption of SWC	0.100	0.038	2.62***	0.022	0.019	1.13
Total Asset	0.000	0.000	0.94	2.65E-07	1.81E-07	1.46
Livestock TLU	0.015	0.012	1.25	-0.006	0.006	-1.03
Crop diversification	0.008	0.024	0.33	-0.014	0.011	-1.23
Coping strategy index	-0.003	0.004	-0.68	0.001	0.002	0.40
Number of Sick	0.038	0.028	1.39	-0.006	0.014	-0.40
Received credit	0.094	0.057	1.66*	0.020	0.028	0.71
Contact with DA	2.90E-04	0.009	0.03	4.70E-04	0.004	0.12
_cons	8.384	0.122	68.68***	0.162	0.060	2.68***
F(19, 388)=8.12				F(19, 388)=1.51		
Prob > F=0				Prob > F=0.077		
R-squared=0.304				R-squared=0.044		
Root MSE=0.335				Root MSE=0.163		

***, ** and * significant at the 1, 5 and 10 percent probability levels, respectively

Table 10 Second stage ESR estimates result

Variables	PCFCE (Birr)				Food insecurity				VFI			
	Adopters		Non-adopters		Adopters		Non-adopters		Adopters		Non-adopters	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Sex	-426.321	260.946	-174.221	444.679	2.061	0.608***	-0.336	0.296	-0.486	0.461	0.434	0.495
Age	-33.564	7.546***	0.639	7.674	0.046	0.011***	0.010	0.008	0.058	0.012***	0.075	0.016***
Education	-30.069	36.222	8.492	35.361	0.082	0.044**	0.013	0.038	-0.126	0.076***	0.016	0.059
Family size	-254.154	47.564***	-356.325	86.037***	0.248	0.065***	0.249	0.060***	1.095	0.144***	1.260	0.161***
DPR	-0.623	1.216	2.584	1.139**	0.002	0.001*	-0.002	0.001	-0.005	0.002*	-0.004	0.002**
Use fertilizer	207.537	208.906	15.590	224.804	0.315	0.255	-0.145	0.237	-1.440	0.355***	-0.701	0.347**
Distance FTC	-2.492	3.252	-4.595	2.490*	0.009	0.004***	0.002	0.003	0.004	0.004	-0.006	0.003*
Numbers of plot	273.262	113.885**	-103.980	115.713	-0.487	0.161***	0.044	0.144	-0.201	0.211	-0.113	0.221
Use of irrigation	38.457	211.661	411.458	192.417**	0.405	0.262	-0.568	0.228**	-0.666	0.318**	-1.500	0.377***
Cultivated land	-584.153	564.800	2397.716	934.104**	1.295	0.671*	-1.345	0.764*	-1.443	0.980	-4.610	1.230***
TLU	34.674	45.871	84.649	46.484*	-0.084	0.072	-0.111	0.053**	-0.289	0.101***	-0.272	0.068***
Received credit	102.810	292.532	413.881	369.584	0.435	0.335	-0.525	0.322	-1.852	0.602***	-1.129	0.427***
Off-farm	330.742	196.487*	-442.868	176.937**	0.426	0.250*	0.152	0.200	-0.043	0.331	0.510	0.300*
Erosion problem	-219.123	237.879	124.210	179.242	0.925	0.286***	0.151	0.204	-0.091	0.407	0.371	0.318
IMR	-643.589	569.941	99.487	411.321	1.807	0.683***	-0.410	0.529	-1.207	0.869	0.646	0.678
_cons	6938.765	1058.708***	4627.157	617.019***	-8.760	1.711***	-1.447	0.552***	-5.360	1.621***	-7.439	1.135
Number of obs.	200		208		200		208		200		208	
F-Value/Wald Chi2	6.62		3.68		65.430		33.010		87.390		76.980	
Prob > F	0		0		0.000		0.005		0.000		0.000	
R-squared/Pseudo r2	0.3146		0.260		0.299		0.139		0.653		0.619	
Root MSE	1207.4		1388.9									
Log pseudo likelihood					-84.949		-121.968		-42.944		-54.653	

***, ** and * significant at the 1, 5 and 10 percent probability levels, respectively

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