Received 26 October 2017
Revised 30 January 2018
24 August 2018
6 November 2018
Accepted 20 December 2018

The effect of climate change adaptation strategy on farm households welfare in the Nile basin of Ethiopia

Is there synergy or trade-offs?

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Abstract

Purpose – This study aims to examine the effect of crop diversification (CD), as a climate change adaptation strategy, on farm household's welfare in terms of farm income and demand for labor. It explores whether adoption of CD is a win-win strategy on household income and demand for on-farm labor. It also examines the determinants of rural household's net farm income and family labor demand.

Design/methodology/approach – A household-plot level data were collected in 2015 from 929 rural farm households and 4,778 plots in the Nile Basin of Ethiopia. The data comprise farm and household characteristics accompanied by geo-referenced climate data such as long-term average temperature and amount and variability of growing season rainfall. The authors estimate an endogenous switching regression model to measure the effect of CD on the farm household's welfare, using net farm income and household labor demand as a welfare indicator.

Findings – The results indicate heterogeneous effects of climate variables on farm income between adopters and non-adopters of CD. The study also confirms the win-win effect of adoption of CD with a positive and significant effect on farm income and a reduction in demand for on-farm labor. The results suggest that adoption of CD helps improve the well-being of farm households and build a resilient agricultural system.

Research limitations/implications – As the study used a cross-sectional data, it is limited to show the time effect of practicing CD on the household's welfare.

This study was financed by the International Development Research Centre (IDRC) under the project "Adaptation to Increase Resilience to Climate Change in Ethiopian Agriculture (IDRC Project Number: 107745-001)". Logistical support for this study from the Environment and Climate Research Center (ECRC) at the Ethiopian Development Research Institute (EDRI) is also gratefully acknowledged. Comments from anonymous referees of this journal are also highly appreciated.

International Journal of Climate Change Strategies and Management
Vol. 11 No. 4, 2019
pp. 518-535
Emerald Publishing Limited
1756-8692
DOI 10.1108/IJCCSM-10-2017-0192

Originality/value – First, the authors investigate, to their knowledge for the first time, the existence of synergy or tradeoff in the effect of CD on two dimensions of rural households' welfare (net farm income and labor demand). Second, they investigate the heterogeneous effect of climate change adaptation strategies on the farm household's welfare between adopters and non-adopters. This is unlike previous studies that consider climate change adaptation strategies as having a homogeneous effect. However, this approach is inappropriate since the effect of adaptation strategies is different for adopters and non-adopters.

Keywords Climate change, Household welfare, Crop diversification (CD), Endogenous Switching Regression model (ESRM), Effect of climate change

Paper type Research paper

1. Introduction

Climate change is one of the most critical problems facing the world. Developing countries are severely affected by climate change partly because many of these are heavily dependent on agriculture as their source of income which is highly vulnerable to climate change effects. Africa is expected to lose 0.13 to 2 per cent of its GDP by 2100 because of the negative effect of climate change on agriculture. The continent is the least equipped financially and technically to adapt to changing conditions and lagging behind in the adoption of improved technologies like irrigation, capital and high yield varieties [United Nations (UN), 2007; Intergovernmental Panel on Climate Change (IPCC), 2014].

Ethiopian agriculture accounts for about 40 per cent of GDP, 73 per cent of employment and nearly 80 per cent of foreign export earnings [Agricultural Transformation Agency (ATA), 2014; Federal Democratic Republic of Ethiopia (FDRE), 2016]. The sector is challenged by many factors, of which climate-related disasters like drought and floods are the major ones (Deressa, 2007; Elias, 2016). Temperature is projected to increase by 1.7-2.7°C in the year 2050, which is very damaging and dangerous. Ethiopia's GDP is projected to be 10 per cent lower compared to the no climate change scenario in the 2040s (Robinson *et al.*, 2012). In the literature, it is suggested that taking adaptation measures will help reduce the effect of climate change (Bradshaw *et al.*, 2004; Lin, 2011; Teklewold *et al.*, 2013; Di Falco *et al.*, 2011). However, the adoption of climate change adaptation measures is very limited in Ethiopia (Deressa, *et al.*, 2008; Di Falco *et al.*, 2011). In the study area, agriculture is predominantly rain-fed with about 1 per cent of households using irrigation water. About 58 per cent of farm households do not practice adaptation measures to address climate-related shocks (Di Falco *et al.*, 2011). Climate change adaptation strategies are mainly aimed at increasing the productivity of farmers under changing climatic conditions which help farmers to attain food security and alleviate poverty.

In this study, we consider the application of crop diversification (CD) as a climate change adaptation measure. CD via intercropping and crop rotation is a strategy for attempting to grow and manage more than one crop across space or time which involves the exploitation of jointly beneficial interactions among individual crops. These include reducing the incidence of weeds, pests and diseases; improving soil fertility, organic matter content and water-holding capacity; diversifying the seasonal requirements of resources; and stabilizing farm income over time through evening out the impact of price fluctuation. (Liebman and Dyck, 1992; Snapp *et al.*, 2010; David *et al.*, 2002; Jhamtani, 2011; Woodfine, 2009). This practice is often considered as a key component of integrated soil fertility management and integrated pest management strategies for smallholder farmers. This can save farmers the cost of buying fertilizer and pesticides, which contributes to the mitigation of climate change and reduce labor demand for pest and weed control (Knowler and Bradshaw, 2007; Fuglie, 1999). CD also enables farmers to grow products that can be harvested at different times and in different places and that have different weather or environmental stress-response characteristics. Hence, multiple cropping serves as a hedge against the risk of drought, extreme or unseasonal temperatures, rainfall variations and price fluctuations that affect the productivity and income of smallholder systems. Accordingly, several studies provide empirical evidence on the contribution of CD to the farmers. Teklewold *et al.* (2013) found that system diversification reduces farmers' use of nitrogen fertilizer and pesticide, because of nitrogen fixation by the legume crops, and diversification controls pests, weeds and disease.

Moreover, Liebman and Dyck (1992); Azevedo *et al.* (1999); Campbell *et al.* (1991) and Stanger and Lauer (2008) found that crop rotation can improve crop yield significantly. This is attributed to the existence of a large amount of N concentration under different rotation sequences. It also plays a paramount role in managing weed, pests, insects and crop diseases. (Cavigelli *et al.*, 2013; Prasifka *et al.*, 2006). Even though CD through crop rotation has important agronomic and economic benefits, studies that empirically examine the joint benefits are limited. For instance, Tibesigwa *et al.* (2015); Afolami *et al.* (2015); Kuntashula *et al.* (2014); Bola *et al.* (2012) and Asfaw (2010) showed that climate change adaptation measures like CD can improve household's welfare. However, in these studies, welfare is measured in terms of either household's consumption expenditure or farm income. However, if we look at the household's decision to maximize welfare, they will maximize welfare subject to a budget constraint which takes in to account the price of outputs and purchased inputs, and the time endowment of each household member (Koihlin and Amacher, 2005). This dimension of welfare is very important because a given farm household might not only maximize its utility by having higher farm income or consumption level alone. Rather, he/she may be highly satisfied by having a discussion or other social activities with family or the local community.

The concept of synergy and tradeoff is discussed mainly in the literature outside climate change adaptation and household's welfare (Balagamwala *et al.*, 2015; Power, 2010; Turkelboom *et al.*, 2016). However, there are no studies yet that try to explore the existence of synergy or tradeoff by adopting CD. In this study, synergy and tradeoff[1] are defined following the approach developed by Turkelboom *et al.* (2016).

A trade-off will exist if adoption of CD directly increases net farm income and family labor time. A synergy, on the other hand, is a situation where adoption of CD can increase net farm income and decrease family labor time.

Thus, in this paper, we analyze the effect of CD[2] on rural farm household's welfare by considering on-farm labor demand and net farm income as measures of welfare. Specifically, it has the following objectives:

- to examine the differential effect of climate variables and other socio-economic factors on farm income and on-farm labor demand among adopters and non-adopters of CD;
- to explore the average adoption effect of CD on farm income and on-farm labor demand; and
- to show whether adoption of CD is win-win in terms of effects on farm income and on-farm labor demand.

The rest of the paper is organized as follows. Section 2 provides a brief description of the data. Section 3 presents the conceptual and econometric framework we use for adoption selection model and estimation of average treatment effects. This is followed by a presentation of the empirical specification of our estimation model in Section 4. In Section 5, we discuss our estimation results. Section 6 concludes and presents key findings and policy implications.

2. The data and definition of variables

The study uses primary data collected using a structured questionnaire from 929 farm households and 4,778 plots within the Nile basin of Ethiopia by the Environment and Climate Research Center (ECRC) at the Ethiopian Development Research Institute (EDRI) in 2015. The data comprise household characteristics, land characteristics, credit, social capital, adaptation practices and perceptions of climate change. The study incorporated different climate variables in the empirical model. The average monthly temperature (°C) and the average growing season rainfall (mm) from 2000 to 2013 are included as prime factors. Monthly rainfall and temperature data were collected from all the meteorological stations in the country. Then, the Thin Plate Spline[3] method of spatial interpolation was used to impute the household-specific rainfall and temperature values using latitude, longitude and elevation information of each household. This method is one of the most commonly used to create spatial climate data sets. Its strengths are that it is readily available and relatively easy to apply, and it accounts for spatially varying elevation relationships (Di Falco *et al.*, 2011).

The sampling frame considered the traditional typology of agro-ecological zones in the country (namely, Dega, Woina-Dega, Kolla and Berha)[4]. The following variables were also considered to select sample districts purposely: percentage of cultivated land, the degree of irrigation activity, average annual rainfall, rainfall variability and vulnerability (measured as number of food aid-dependent population). Woredas were selected in such a way that each class in the sample matched to the proportions for each class in the entire Nile basin of Ethiopia. Following this procedure, 20 woredas were selected purposely and simple random sampling was then used in selecting one village from each woreda and 50 households from each village. A part of the survey instrument was in particular designed to capture farmers' perceptions and understanding of climate change and their approaches for adaptation.

3. Conceptual and econometric framework

The conceptual framework of this study dates back to the study of Roy (1951). In his study, Roy showed how individuals self-select themselves between two different occupations, hunting and fishing, based on their comparative advantage. The decision to participate in either of the two occupations is conditional on the benefit that will be generated from the occupations (Maddala, 1986).

Similarly, farm households will practice a given adaptation strategy by their own will. Households will self-select in their decision to adopt a given strategy. However, the decision to practice a given adaptation strategy will depend on the expected utility of adoption. The farmer will practice a given adaptation strategy if the utility from that strategy is greater than alternative strategies. Thus, the decision to adopt adaptation strategies can be modeled in a random utility framework (Kassie *et al.*, 2011; Di Falco *et al.*, 2011; Asfaw, 2010).

Let the difference in utility from adoption (U_{hA}) and non-adoption (U_{hN}) be denoted by Th*. However, the utilities are unobservable and this is represented by the following latent variable model:

$$T_h* = \beta_{Zh}\ Z + \mu_h, T_h = 1 \quad if\ T_h* > 0 \tag{1}$$

where:

$T_h* = U_{hA} - U_{hN}$ is unobservable;

$T_h = 1$ if a farmer practices at least one of the given adaptation strategies;

$T_h = 0$ otherwise β_{Zh} = vector of parameters;

Z_h = vector of explanatory variables; and

μ_h = the error term.

Now if we assume the relationship between an outcome variable such as net agricultural income and adaptation strategies is linear, this may be represented by:

$$Y_h = \gamma X_h + \delta T_h + \varepsilon_h \tag{2}$$

where,

Y_h is an outcome variable such as net agricultural income;

γ and δ are vectors of parameters to be estimated and ε_h is the error term.

If we run the above regression, the coefficient of adoption is δ, which measures the impact of practicing a given adaptation strategy on the outcome variable. Yet, this measurement is not accurate. To be taken as an appropriate measure, the decision to practice adaptation strategies should be random. In other words, the groups of adopters and non-adopters should be randomly assigned. However, in the case of practicing climate change adaptation measures, farmers will decide to practice each adaptation strategy by their own consent. Thus, there is a problem of self-selection which leads to selection bias. The decision to take a given adaptation measure is likely to be affected by unobservable characteristics such as managerial skill, average land fertility and motivation that may be correlated with the outcome of interest.

From a regression perspective, this is similar to saying ε is correlated with T or μ. If this is the case, the specified equation above fails to account for self-selection, ending up with a biased result.

Therefore, the appropriate approach is to follow a model that takes in to account selection bias correction. In the literature on selection, different bias correction methods have been proposed and used. Mainly, the works of Lee (1983); Dubin and Mcfadden (1984) and semiparametric alternatives proposed by Dahl (2002) are noticeable. However, the method proposed by Dubin and McFadden is highly preferable to other methods as shown by Bourguignon *et al.* (2007).

In this study, we use an endogenous switching regression model (ESRM) using the Dubin and McFadden method as improved by Bourguignon *et al.* (2007)[5]. This would make the study follow recent advances in the area and lend the outcomes of the study for comparison with recent studies. Recently, the approach has been used by several researchers including Di Falco *et al.* (2010); Kassie *et al.* (2015); Teklewold *et al.* (2013) and Di Falco *et al.* (2011).

3.1 Adoption selection model

A representative farm household will choose to adopt CD if the expected utility from adopting is greater than the expected utility of not adopting. Now let A* be the latent variable that captures the expected benefits from the choice of CD practice compared with not choosing this practice. The criterion (selection) equation would then be described as:

$$\mathrm{A}_\mathrm{i}^* = \mathrm{X}_\mathrm{i}\beta + \varepsilon_\mathrm{i}, \text{ with } \mathrm{A}_\mathrm{i} = \begin{cases} 1 \text{ if } \quad \mathrm{A}_\mathrm{i}^* > 0 \\ 0 \text{ other wise} \end{cases} \tag{3}$$

Farm household *i* will choose to practice CD ($\mathrm{A}_\mathrm{i} = 1$) in response to long term changes in mean temperature and rainfall if $\mathrm{A}_\mathrm{i}^* > 0$, and will not practice otherwise. The vector X represents variables that affect the likelihood to practice such as the characteristics of the operating farm, farm head and farm household's characteristics, presence of assets, past climatic factors, experience with previous extreme events, whether farmers received information on CD, government and farmer-to-farmer extension and other institutional factors such as credit and land tenure.

In overcoming the standard econometric problem associated with the use of a pooled sample of CD adopters and non-adopters, we use ESRM framework for household net farm income which is proxied by net revenue per hectare. Accounting for endogeneity and selection biases this measure can then be elicited into two estimable functions where farmers face two regimes: To practice CD, Not to practice CD and is defined as follows:

$$\text{Regime 1}: \; Y_{1i} = Q_{1i}\,\alpha_{1i} + \mu_{1i} \quad \text{if } A = 1 \tag{4}$$

$$\text{Regime 2}: \; Y_{2i} = Q_{2i}\,\alpha_{2i} + \mu_{2i} \quad \text{if } A = 2 \tag{5}$$

where Y_i is the outcome variable which is farm household's net farm income in the two regimes and Q_{1i} and Q_{2i} represent a vector of exogenous variables included in X. α_{1i} and α_{2i} are vectors of population parameters that will be estimated in the model using the survey data. Further, our model relies on the assumption that the error terms in equations (3), (4) and (5) have a trivariate normal distribution, with zero mean and covariance matrix of: $\begin{pmatrix} \delta_1^2 & \delta_{1\varepsilon} & \delta_{2\varepsilon} \\ \delta_{1\varepsilon} & \delta_2^2 & * \\ \delta_{2\epsilon} & * & \delta_\varepsilon^2 \end{pmatrix}$ where δ_1^2 and δ_2^2 are variances of the stochastic disturbance terms in the regime functions in equations (4) and (5). δ_ε^2 is the variance of the stochastic disturbance term in the selection equation shown as equation (3). * represents the covariance of the stochastic disturbance terms in equations (4) and (5) while it is not determined as Y_{1i} and Y_{2i} cannot be observed simultaneously. $\delta_{1\varepsilon}$ is the covariance of the error term of selection equation (ε_i) and the outcome equation of regime one (μ_{1i}). Likewise, $\delta_{2\epsilon}$ represents the covariance of the stochastic disturbance terms in the selection equation and the outcome equation of regime two (μ_{2i}). The variance for the error term in the selection equation (δ_ε^2) is assumed to be 1, since the coefficients are estimable only up to a scale factor (Maddala, 1983).

An important implication of the error structure is that, because the error term of the selection equation (4) ε_i is correlated with the error terms of the regime equations (5) and (6), which are μ_{1i} and μ_{2i}, the expected values of these two error terms conditional on the sample selection are nonzero.

Mathematically; $[\mu_{1i}|A_i = 1] = \delta_{1\varepsilon}\frac{\Phi(X_{i\beta})}{\Phi(X_{i\beta})} = \delta_{1\varepsilon}\,\lambda_{1i}$ and $[\mu_{2i}|A_i = 0] = -\delta_{2\varepsilon}\frac{\Phi(X_{i\beta})}{1-\Phi(X_{i\beta})} = \delta_{2\varepsilon}\,\lambda_{2i}$ where ϕ (.) is the standard normal probability density function, Φ(.) the standard normal cumulative function, $\lambda_{1i} = \frac{\Phi(X_{i\beta})}{\Phi(X_{i\beta})}$ and $\lambda_{2i} = -\frac{\Phi(X_{i\beta})}{1-\Phi(X_{i\beta})}$ If $\delta'_{1\varepsilon}$ and $\delta'_{2\varepsilon}$ (estimated covariances) are statistically significant, the decision to practice CD and household's welfare are correlated which becomes evidence for endogenous switching and in turn indicates the existence of sample selection bias. The above model described by equations (3) through (5) is known as a "switching regression model with endogenous switching" (Maddala and Nelson, 1975).

The commonly used approach to estimate models that involve self-selection is by following the two-stage procedure. However, this method is inappropriate and highly criticized because it requires some adjustment to derive consistent standard errors and it shows poor performance when there is high multicollinearity between the covariates of the selection equation and the covariates of the outcome equation (Maddala, 1983) The appropriate and efficient method to estimate ESRMs is full information maximum likelihood (FIML) estimation. This method is preferable to other approaches in many instances. First, it is feasible with available software and it provides an efficient estimate. In addition, it allows restrictions to be applied and permits construction of likelihood ratio tests on the restriction (Lee and Trost, 1977; Mare and Winship, 1987) When similar variables affect the adoption decision (X) and the subsequent outcome equations (Q), lack of identification of the model will be a problem. Even though non-linear correction terms are included, this may not be enough and results in the problem of multicollinearity (Khanna, 2001; Babcock and Jie, 1998). To overcome this problem finding an instrumental variable is very tedious and difficult, if not impossible. Therefore, to assure the admissibility of the model, we have used exclusion restrictions. These variables are hypothesized to affect directly the selection variable but not the outcome variable. Variables related to information sources like government extension, farmer-to-farmer extension, and information from radio, and input market distances are used in the welfare function. The admissibility of these instruments is established by performing a simple falsification test, i.e. if a variable is a valid selection instrument then it will affect the decision of choosing an adaptation strategy but it will not affect the net revenue per hectare among farm households that did not adopt. The logarithmic likelihood function given the previous assumptions regarding the distribution of the error terms is:

$$lnL_i = \sum_{i=1}^{N} A_i\left[\ln\phi\left(\frac{\varepsilon_{1i}}{\delta 1}\right)\right] - ln\delta_1 + ln\ \Phi(\Upsilon_{1i}) + (1-A_i)\left[\ln\phi\left(\frac{\varepsilon_{2i}}{\delta 2}\right) - ln\delta_2 + \ln((1-\ \Phi)\ (\Upsilon_{2i}))\ \right] \tag{6}$$

where $\Upsilon_{ij} = \frac{\left(X_{i\beta}\,\rho_{ji}/\delta_1\right)}{\sqrt{1-\rho_j^2}}$ j = 1, 2 with ρ_j = the correlation coefficient between ε_i (the error term of the selection equation) and the error term μ_{ji} of the outcome equations (5) and (6).

3.2 Estimation of average treatment effects and counter-factual analysis

ESRM is very important to compare the expected welfare of farm households that adopted CD (7a) to farm households that did not adopt (7b). It is also used to investigate the expected farm household welfare in the counterfactual case, that is, when farm households who have adopted CD did not adopt (8a), and when farm households that had not adopted did adopt (8b). Following this approach not only solves selection bias because of unobserved heterogeneity, but it also controls for selection bias because of observed heterogeneity.

The conditional expectations for household welfare in the four cases can be expressed as:

(1) Adopters with adoption (actual adoption observed in the sample):

$$E(Y1i/Ai=1) = \mathrm{Q_{1i}}\ \alpha_1 + \delta_{1\varepsilon}\lambda_{1i} \tag{7a}$$

(2) Non-adopters without adoption:

$$E(Y2i/Ai=0) = \mathrm{Q_{2i}}\ \alpha_2 + \delta_{2\varepsilon}\lambda_{2i} \tag{7b}$$

(3) Adopters had they decided not to adopt:

$$E(Y1i/Ai=0)=Q_{2i}\ \alpha_1+\delta_{1\varepsilon}\lambda_{2i} \quad (8a)$$

(4) Non-adopters had they decided to adopt:

$$E(Y2i/Ai=1)=Q_{1i}\ \alpha_2+\ \delta_{2\varepsilon}\lambda_{1i} \quad (8b)$$

The expected values derived above help to calculate unbiased estimates of TT. We can define the treatment effects as the difference between (7a) and (8b) or (7b) and (8a) i.e.:

$$TT\ =E(Y1i/Ai=1)-\ E(Y2i/Ai=1)$$

$$TT=Q_{1i}(\ \alpha_1-\ \alpha_2)+(\delta_{1\varepsilon}-\delta_{2\varepsilon}\ )\ \lambda_{1i} \quad (9)$$

By following similar procedure, we can also calculate the effect of adoption on the non-adopters (TU) which is the difference between (7b) and (8a), i.e.:

$$TU=E(Y1i/Ai=0)-\ E(Y2i/Ai=0)$$

$$TU=Q_{2i}(\ \alpha_1-\ \alpha_2)+(\delta_{1\varepsilon}-\delta_{2\varepsilon}\ )\ \lambda_{2i} \quad (10)$$

The difference between (TT) and (TU) in equations (9) and (10) represents the so-called “transitional heterogeneity” (TH) which indicates whether the effect of adopting CD is larger or smaller for the adopters than for the non-adopters.

4. Results and discussion

4.1 Determinants of farm household’s net income

For the analysis of the determinants of farm household’s net income discussed here as well as farm labor demand discussed in the next sub-section, we estimate the ESRM using FIML estimation technique. The discussion of results focuses on the role of climate variables. The results are shown in the Appendix.

Both average rainfall and temperature are expected to have a nonlinear effect on farm income of adopters and non-adopters. Therefore, average temperature and rainfall with their respective squares are included in this study. As per the expectation, the effect of temperature is found nonlinear and significant.

A unit’s increase in temperature increases the income of both adopters and non-adopters. However, the income of adopters is increased by a larger amount than the non-adopters. This is because of the fact that the non-adopters’ farm income is compromised by the effect of high temperature. On the contrary, adopters of CD become beneficiary since CD reduces the effect of high temperature on crop yield by conserving moisture and increasing soil fertility.

After some point, income tends to decline for both adopters and non-adopters as temperature increases as shown by the negative sign of temperature square. This result also confirms the advantage of adopting CD. This is because when we look at the turning point for the inverted u-shape relationship between temperature and farm income, the inflection point for adopters is found 10 per cent larger than the non-adopters. In other words, farm household income of adopter’s increases for 10 per cent amount even after the non-adopter’s income starts to decline because of the higher temperature. This implies that adoption of CD can help farm households to reduce the effect of climate change on their farm net revenue. Similar studies have also shown that climate change affects farm income negatively. For instance, Lee and Nadolnyak (2012) indicated that in USAA though an increase in temperature boosts farm profit initially, it has a negative effect when farmers join the highly drier climate scenario. Bobojonov and Aw-Hassan (2014) also found a similar result for Central Asia.

Moreover, Quiroga and Suárez (2016) reported that higher temperature and lower precipitation also negatively affect agricultural income distribution in Spain. Results of studies in Ethiopia are also similar (Deressa, 2007; Aragie, 2013; Gebreegziabher *et al.*, 2011). On the other hand, increase in average rainfall reduces the income of farm households for both adopters and non-adopters. This suggests that CD is most effective in low rainfall or drier areas.

Apart from this, rainfall and temperature variability are crucial factors that affect farm household's income. This suggests that even if the total amount of rain during a given production year is enough, its timing and distribution is vital. If all of the total rain needed for one production season rained at the beginning of the production period, it will be harmful for farmers. Thus, giving attention to rainfall variability is very important.

The results of the study show that both rainfall and temperature variability are found significant determinants of household farm income for both adopters and non-adopters. When the variability of rainfall increases the income of both adopters and non-adopters will decline. However, the reduction in income is significantly smaller for adopters (−6.4) than for non-adopters (−8.2). Similarly, the negative effect of an increase in temperature variability on household income is smaller for adopters (−52.2) than for non-adopters (−70.2). Shumetie and Alemayehu (2017) also found that rainfall variability in the cropping season has a significant negative effect on farm income. Silva and Matyas (2014) and Moylan (2012) found that high rainfall variability reduces farm income for Mozambique and Malawi respectively.

Two related implications of these results are: first, in addition to average rainfall and temperature, attention should be paid to their variability; second, CD has not only the advantage of increasing farm household's income when there is a change in average temperature and rainfall, but it can be the best buffer strategy during times of high temperature and rainfall variability.

In addition to the climate variables, other socio-economic and farm-related factors are also found significant determinants of household income. Factors with negative and significant effects on farm household income adopters and non-adopters are family size, size of cultivated land and livestock ownership. Similar to this result, studies by Qasim (2012) and Moylan (2012) revealed that higher land size is associated with reduced farm income in Pakistan and Malawi respectively. This might be because of the fact that, farmers will fall short of raw materials and agricultural inputs like labor and fertilizer to use when their cultivated land is large. Because of this, farmers will prefer to cultivate intensively in the given small plot of land. From the plot related variables incorporated in this study, land tenure and fertility are found positive and significant determinants of farm household income of adopters and non-adopters. The study by (Kabubo-Mariara *et al.*, 2010) stressed the importance of tenure security to increase the productivity of farmers.

4.2 Determinants of farm household labor

In this section, we discuss the determinants of farm household labor focusing on the role of climatic factors[6]. As noted above, the results are presented in the Appendix.

The effect of temperature on family labor is found nonlinear and significant for both adopters and non-adopters. Initially farm household's labor increases with an increase in temperature but after some point, it exhibits an inverse relationship. This is because when the temperature increases farmers will take different measures to hedge from the effect of high temperature like water conservation activities. However, when the effect of temperature becomes overwhelming, farmers will search for other nonfarm and off-farm employment opportunities. In addition to this, rainfall variability is also found to be negative and significant determinant for family labor demand. This negative relationship would be attributed to the fact that farmers will opt to use their labor in another alternative income generating activities than working on their own land to reduce the negative effect of high rainfall variability on their production. Thus, there will be a reduction in family labor use for the farming activity. Maurel and Kubik (2014) reported a similar result that the total labor devoted to off-farm agricultural work increases when there is an increase in total rainfall in India. In addition, Badiani and Safir (2010) showed that when there is an increase in temperature, farm households send their family members to other places to diversify their income other than working on their own land. The effect of some of the control variables is also significant as can be seen from the results in the Appendix (Table I).

Variables	Description	Non-adopters Mean	Non-adopters SD	Adopters Mean	Adopters SD	Mean Difference
Household characteristics						
FMSIZ	Family size (AE)	7.96	0.3	8.30	0.31	−0.339***
AGE	Age of the head	50.59	12.9	52.34	12.81	−1.74***
MARITAL	1 = if married	1.58		1.46		0.120***
REMIT	1 = received remittance	1.87		1.873		−0.0033
OFFFAR M	1 = if participated in off farm activity	1.77		1.81		−0.038***
GENDER	1 = if the head is male	1.12		1.11		0.016**
EDUC	years of education of the head	2.21	3.13	1.66	2.85	0.557***
Assets and institutional factors						
VPFA	Total value of productive farm assets (ETB)	24342	35810	26086	42814	−1743.96*
FARMSIZE	Farm size (ha)	2.06	1.52	1.97	1.33	0.082*
TLU	Livestock herd size	4.63	3.69	4.92	3.5	−0.294***
CREDIT	1 = Credit constrained (credit is needed but unable to obtain)	0.44		0.43		0.007
FARMSUPPORT	1 = if the household received farm equipment's from the government or NGOs	0.08		0.07		0.010
TENURE	1 = if the land is certified	1.28		1.21		0.068***
GOVEXT	1 = if received government extension service about CD	1.65		1.65		000

Notes: A test used to compare the means of explanatory variables between adopters and non-adopters under the assumption of unequal variance. SD is standard deviation; ***, **, * show difference between adopters and non-adopters is significant at 1, 5 and 10 per cent levels, respectively. Shock index is calculated by dividing the number of shocks that happened on a plot by seven. These shocks are drought, flood, erratic rainfall, animal attack

Table I. Definition and summary statistics of variables

4.3 Average adoption effect of crop diversification

Table II presents the average effect of the adoption of CD on farm income and family labor demand. The number in the first row and first column of Table III is the average income value (3715.63 Birr) for adopters of CD. The number in the second column of the first row (3137.23 Birr) indicates the average net farm revenue for adopters in the counterfactual case. So, the adoption effect on adopters can be found by subtracting the second from the first (578.54 Birr ***). The result is positive and significantly different from zero which suggests that the farm household's income for those who adopted CD is significantly higher than if they did not adopt. By using a similar procedure, the adoption effect of CD on non-adopters can be calculated from Table III. In the second row and first column of Table III, we find the value of net farm income for non-adopters in the counterfactual case, while the second column in the same row represents the same value in the actual case. Thus, the difference between these two cells of the second row gives us farm income of non-adopters (1566.55 Birr ***). The result indicates that net farm income will increase significantly if they adopt CD than the actual case of non-adoption. Tibesigwa *et al.* (2015); Afolami *et al.* (2015); Bola *et al.* (2012) and Asfaw (2010) showed that climate change adaptation measures like CD

Variables	Description	Non-adopters Mean	Non-adopters SD	Adopters Mean	Adopters SD	Mean Difference
Plot characteristics						
PLOTDIST	Plot distance from home in minutes	13.2	16.65	15.41	19.34	−2.16***
SLOPE	*Slope of the plot*					
	1 = flat	0.58		0.61		−0.030**
	2 = medium	0.77		0.69		0.072***
	3 = steep	0.08		0.10		−0.017
FERTILITY	*Fertility of the plot*					
	1 = highly fertile	1.00		1.17		−0.166**
	2 = medium fertility	1.07		0.98		0.086***
	3 = infertile	0.12		0.11		0.0127
SHOCK[a]	Index of shocks the household faced (Numbers)	0.102	0.06	0.102	0.04	000
MEDIA	1 = if the household received media information about CD	0.26		0.19		0.07***
INPUTMAR	Walking distance in minutes	10.47	1.81	10.41	1.92	0.060
ORGANIC	manure used in KG	0.26	0.44	0.23	0.42	0.032***
PESTICIDE	pesticide used in lt	0.1	0.69	0.12	0.65	−0.02
Climate variables						
TEMP 0013	Average annual temperature (^{0}C) 2000-2013	20.02	2.55	19.92	2.58	0.102*
RAIN0013	Average growing season rainfall 2000-2013 (mm)	684	239	707	231	−23.5***
CV TEMP	Coefficient of variation for annual temperature 2000-2013 (mm)	0.1037	0.025	0.101	0.0004	0.0017**
CV RF	Coefficient of variation for average growing season rainfall 2000-2013 (mm)	0.557	0.247	0.534	0.234	0.022***

Notes: [a]Landslide, hailstorms, and other shock specified by the respondent. More shocks on a plot means the shock index will increase approaching 1 as the number of shocks approaches 7; ***significant at 1% level; **significant at 5% level; *significant at 10% level

Table II.
Plot characteristics and climate variables

improve household's welfare. Similar results were also reported by Kuntashula *et al.* (2014); Di Falco *et al.* (2011); Bhattacharyya (2008) and Bradshaw *et al.* (2004).

By following a similar procedure like the one for farm income analysis we did above, the average expected farm household's labor demand in the actual and counterfactual case is estimated for both adopters and non-adopters. This estimation helps to know specifically the treatment effect on adopters (TT), treatment effect on non-adopters (TU) and also the TH.

The number in the first row and first column of Table IV is the average family labor demand (32.85) for adopters of CD. The number in the second column of the same row (90.67) indicates the average household labor for adopters had they been non-adopters. Then the adoption effect on adopters can be found by subtracting the second from the first (−57.82***). The result is negative and significantly different from zero. This indicates that farm households can save 57.82-person days/hectare by adopting CD.

By using a similar procedure, the adoption effect of CD on non-adopter's family labor demand can be calculated from Table III. In the second row and first column of Table IV, we find farm household's labor demand for non-adopters in the counterfactual case, while the second column in the same row shows the value in the actual case. Thus, the difference between these two columns of the second row gives farm household labor demand of non-adopters (−14.29***). The result shows that non-adopter farm households can get an advantage of a reduction in family labor demand amounting to 14.29 person days per hectare if they adopt CD. This is in line with the works of Teklewold *et al.* (2013). Finally, the last cell in the second column gives the value for TH. This value is negative and significantly different from zero (−43.53) implying by adopting CD adopters benefit more than the non-adopters, albeit both are beneficiaries from adoption.

5. Is there synergy or tradeoffs?

In this study, synergy and tradeoffs are defined as follows. Synergy will occur if CD increases net farm income without adding extra labor demand to the household. On the

	Decision stage		
	Adopters	Non-adopters	Adoption effect
Adopters	3715.63 (59.92)	3137.23 (93.47)	TT = 578.54*** (113.45)
Non adopters	2966.75 (80.9)	1400.20 (23.46)	TU = 1566.55*** (62.62)
TH effect			TH = −988.01

Notes: TT = Adoption effect for adopters, TU = Adoption effect for non-adopters, TH (TT-TU) = transitional heterogeneity; ***significant at 1% level; **significant at 5% level; *significant at 10% level

Table III. Adoption effects of CD on net farm income

	Decision stage		
	Adopters	Non-adopters	Adoption effect
Adopters	32.85 (0.30)	90.67 (1.43)	TT = −57.82*** (1.00)
Non-adopters	17.76 (0.15)	32.05 (0.51)	TU = −14.29*** (0.40)
TH effect			TH = −43.53

Notes: TT = Adoption effect for adopters, TU = Adoption effect for non-adopters, TH (TT-TU) = transitional heterogeneity; ***significant at 1% level; **significant at 5% level; *significant at 10% level

Table IV. Adoption effects of CD on family labor demand other hand, there will be a tradeoff when CD increases both net farm income and family labor demand. Either synergy or trade-off is expected to happen between increasing farm household's welfare by boosting productivity and the extra labor burden on household labor use which results from the adoption of CD. Therefore, in this section, we discuss whether there is synergy or tradeoffs.

As can be seen from the results in Tables III and IV, adoption of CD increases net farm income by 578.54 Birr per hectare for adopters and 1566.55 Birr per hectare for non-adopters had they been adopters. Moreover, the reduction in family labor because of the adoption of CD is 57.82 person days for adopters and 14.29 for non-adopters had they been adopters. In both of the two cases, the result indicates the double benefit of adopting CD and they are statistically significant.

Thus, the study revealed that CD not only reduces the total per hectare family labor use but it also increases net farm income. Therefore, it can be taken as a strategy to maximize household's welfare both in terms of making more labor time available for either leisure or other activities and net farm income. By doing this CD as an adaptation strategy helps reduce the effects of climate change and improve farm households' welfare.

6. Concluding remarks

The general objective of this study is to examine the effect of CD on farm households' welfare, more specifically on family labor use and net farm income. The study used the 2015 survey database on 929 farm households collected in Nile Basin of Ethiopia by ECRC/EDRI. Our final analysis includes 4778 plots. To estimate the adoption effect on net farm income and farm labor demand along with the determinants of household net farm income and the adoption decision, simultaneous equation model which can capture the unobserved heterogeneity and selection bias was estimated. The following main conclusions can be drawn from the results of the study.

First, it was found that climate variables, household and plot characteristics are the main determinants of farm income and household labor demand. Farm income of adopters and non-adopters is positively determined by temperature. However, the income of adopters is increased by a larger amount than the non-adopters. Thus, it is vital to work on the promotion and expansion of CD through the provision of extension services to better use CD as a hedge for higher temperature. In addition, family size, cultivated land size, and livestock ownership are found negative determinants of farm income. Family labor demand is found to be determined by average temperature positively and significantly. However, rainfall variability affects the demand for family labor negatively.

Second, for both adopters and non-adopters diversifying crop can spur farm households' welfare had they decided to adopt than they would if they had not adopted. In addition, non-adopters can get a larger payoff relative to adopters if both of the two groups decided to adopt.

Third, the average treatment effect of adopting CD on family labor use is also significant for both adopters and non-adopters had they been adopters. By adopting CD, farmers reduce their workload on their family and get extra time for leisure and other activities. In relative terms, the adopter's labor reduction is larger than the non-adopters.

Finally, adoption of CD provides a double benefit for both adopters and non-adopters. For both groups, it can reduce family workload and increase the well-being of farm households through an increase in net farm income. Thus, by adopting CD there is synergy than tradeoffs. An important policy implication of this is that the current agricultural extension program could focus on the promotion of and support for the adoption of CD to rescue rural farmers from the negative effect of climate change. Even though both adopters and non-adopters benefit from adoption of CD, the extent of the treatment effect is not the same. This is an indication of the discrepancy that exists between adopters and non-adopters. Therefore, policymakers should take into consideration this heterogeneity when they are attempting to advance the relevance of CD so as to unleash the full potential benefit of the practice.

7. Limitation of the study

As the study used a cross-sectional data, it is limited to show the time effect of practicing CD on the household's welfare.

Notes

1. See Turkelboom *et al.* (2016) for more discussion on synergy and tradeoff.
2. In this study, we consider crop rotation as crop diversification. Thus, adopters are those who practice crop rotation on a plot in the last cultivation year.
3. By definition, *Thin Plate Spline* is a physically based two-dimensional interpolation scheme for arbitrarily spaced tabulated data. The Spline surface represents a thin metal sheet that is constrained not to move at the grid points, which ensures that the generated rainfall and temperature data at the weather stations are exactly the same as data at the weather station sites that were used for the interpolation. In our case, the rainfall and temperature data at the weather stations are reproduced by the interpolation for those stations, which ensures the credibility of the method (see Wahba, 1990).
4. This classification is based on altitudinal difference (in meters above sea level), i.e, Wurch >3200 meters, Dega 2300 – 3200 meters, Woina-dega 1500 -2300 meters, Kola 500 -1500 meters and Bereha < 500 meters.
5. See Bourguignon *et al.* (2007) for detailed derivation of the specifications and comparisons between different selection bias correction methods.
6. The estimation results for farm income and household labor demand can be found in the Appendix.

References

Afolami, C.A., Obayelu, A.E. and Vaughan, I. (2015), "Welfare impact of adoption of improved cassava varieties by rural households in South Western Nigeria", *Agricultural and Food Economics*, Vol. 3 No. 1, pp. 1-7, doi: 10.1186/s40100-015-0037-2.

Agricultural Transformation Agency (ATA) (2014), *Transforming Agriculture in Ethioipia: Annual Report 2013/2014*, Addis Ababa, available at: www.ata.gov.et/wp-content/uploads/Annual_Report.pdf

Aragie, E.A. (2013), "Climate change, growth, and poverty in Ethiopia", The Robert S. Strauss center for international security and law working paper No (3), Texas university Austin.

Asfaw, S. (2010), "Estimating welfare effect of modern agricultural technologies: a micro-perspective from Tanzania and Ethiopia", Unpublished manuscript, available at: www.chronicpoverty.org/uploads/publication_files/asfaw_agricultural_technologies.pdf

Azevedo, D.M., Vieira, M.R.L.J. and Moseley, D. (1999), "The effect of cover crop and crop rotation on soil water storage and on sorghum yield", *Pesquisa Agropecuária Brasileira*, Vol. 34 No. 3, pp. 391-398.

Babcock, J.A.B. and Jie, J. (1998), "The choice of tillage, rotation, and soil testing practices: economic and environmental implications", *American Journal of Agricultural Economics*, Vol. 80 No. 3, pp. 494-511, available at: www.jstor.org/stable/1244552.

Badiani, R. and Safir, A. (2010), "Coping with aggregate shocks: temporary migration and other labor responses to climatic shocks in rural India", available at: www.researchgate.net/publication/228774326

Balagamwala, M., Gazdar, H. and Mallah, H.B. (2015), "Synergy or trade-off between agricultural growth and nutrition women's work and care", *The Pakistan Development Review*, Vol. 54 No. 4, pp. 897-913, available at: http://pide.org.pk/

Bhattacharyya, R. (2008), "Crop diversification: a search for an alternative income of the farmers in the state of West Bengal in India", *International Conference on Applied Economics*, pp. 83-94.

Bobojonov, I. and Aw-Hassan, A. (2014), "Impacts of climate change on farm income security in central Asia: an integrated modeling approach", *Agriculture, Ecosystems and Environment*, Vol. 188, pp. 245-255.

Bola, A.A., Diagne, A. and Omonoma, B.T. (2012), "Inclusive growth in Africa", A paper presented at the African Economic Conference, 30 October-2 November 2012, Kigali.

Bourguignon, F., Fournier, M. and Gurgand, M. (2007), "Selection bias correction based on the multinomial logit model Monte Carlo analysis", *Journal of Economic Surveys*, Vol. 21 No. 1, pp. 174-205.

Bradshaw, B., Dolan, H. and Smit, B. (2004), "Farm-level adaptation to climatic variability and change: crop diversification in the Canadian prairies", *Climatic Change*, Vol. 67 No. 1, pp. 119-141.

Campbell, C.A., Biederbec, V.O., Zentne, P.R. and Lafond, P.G. (1991), "Effect of crop rotations and cultural practices on soil organic matter, microbial biomass and respiration in a thin black Chernozem", *Canadian Journal of Soil Science*, Vol. 71 No. 3, pp. 363-376.

Cavigelli, M.A., Teasdale, J.R. and Spargo, J.T. (2013), "Increasing crop rotation diversity improves agronomic, economic, and environmental performance of organic grain cropping systems at the USDA-ARS beltsville farming systems project", *USDA Organic Farming System. Plant Management Network, in USDA Organic Farming System Research Conference*, doi: 10.1094/CM-2013-0429-02-PS.Despite.

Dahl, G.B. (2002), "Mobility and the return to education: testing a roy model with multiple markets", *Econometrica*, Vol. 70 No. 6, pp. 2367-2420.

David, T., Cassman, K.G., Matson, A.P., Naylor, R.L. and Polasky, S. (2002), "Agricultural sustainability and intensive production practices", *Nature Insight Review Articles*, Vol. 418, pp. 671-677.

Deressa, T.T. (2007), "Measuring the economic impact of climate change on Ethiopian agriculture: Ricardian approach", Working paper (4342), September, 2007, World Bank (WB), doi: 10.1596/1813-9450-4342.

Deressa, T., Hassan, R.M., Alemu, T., Yesuf, M. and Ringler, C. (2008), "Analyzing the determinants of farmers' choice of adaptation methods and perceptions of climate change in the Nile Basin of Ethiopia", Environment and Production Technology Division, IFPRI Discussion paper 00798, doi: 10.1016/j.gloenvcha.2009.01.002.

Di Falco, S., Bezabih, M. and Yesuf, M. (2010), "Seeds for livelihood: crop biodiversity and food production in Ethiopia", *Ecological Economics*, Vol. 69 No. 8, pp. 1695-1702.

Di Falco, S., Veronesi, M. and Yesuf, M. (2011), "Does adaptation to climate change provide food security? A micro-perspective from Ethiopia", *American Journal of Agricultural Economics*, Vol. 93 No. 3, pp. 825-842, doi: 10.1093/ajae/aar006.

Dubin, J.A. and Mcfadden, D.L. (1984), "An econometric analysis of residential electric appliance holdings and consumption", *Econometrica*, Vol. 52 No. 2, pp. 345-362, doi: 10.1088/0954-898X/15/3/001.

Elias, H. (2016), "Welfare implications of credit constraints and climate change adaptation strategies on Ethiopian farm households", Doctoral dissertation, Addis Ababa University Addis Ababa, Ethiopia. available at: http://etd.aau.edu.et/handle/123456789/13430.

Federal Democratic Republic of Ethiopia (FDRE) (2016), "Growth and transformation plan II (GTP II); volume I", *Addis Ababa*, available at: www.mcit.gov.et/documents/1268465/13533561/FDRE+-+National+ICT+Policy+English.pdf/1a626364-1ef3-424f-97ce-33356ca4628f

Fuglie, K.O. (1999), "Conservation tillage and pesticide use in the Cornbelt", *Journal of Agricultural and Applied Economics*, Vol. 31 No. 1, pp. 133-147.

Gebreegziabher, Z., Stage, J., Mekonnen, A. and Alemu, A. (2011), "Climate change and the Ethiopian economy: a computable general equilibrium analysis". Environment for development discussion paper series (EfD) No. 9, available at: www.diva-portal.org/smash/get/diva2:406612/FULLTEXT01.pdf

Intergovernmental Panel on Climate Change (IPCC) (2014), "Climate change 2014: impacts, adaptation, and vulnerability part A: global and sectoral aspects", *Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*.

Jhamtani, H. (2011), "The green revolution in Asia: lessons for Africa", *Climate Change and Food System Resilience in Sub Saharan Africa*, Vol. 134 No. 4, pp. 635-646.

Kabubo-Mariara, J., Linderhof, V. and Kruseman, G. (2010), "Does land tenure security matter for investment in soil and water conservation? Evidence from Kenya", *African Journal of Agricultural and Resource Economics*, Vol. 4 No. 2, pp. 123-139, doi: 10.2139/ssrn.1527197.

Kassie, M., Shiferaw, B. and Muricho, G. (2011), "Agricultural technology, crop income, and poverty alleviation in Uganda", *World Development*, Vol. 39 No. 10, pp. 1784-1795.

Kassie, M., Teklewold, H., Marenya, P., Jaleta, M. and Erenstein, O. (2015), "Production risks and food security under alternative technology choices in Malawi: application of a multinomial endogenous switching regression", *Journal of Agricultural Economics*, Vol. 66 No. 3, pp. 640-659.

Khanna, M. (2001), "Agricultural and applied economics association sequential adoption of site-specific technologies and its implications for nitrogen productivity: a double selectivity model sequential adoption of site-specific technologies and its implications for nitrogen", *American Journal of Agricultural Economics*, Vol. 83 No. 1, pp. 35-51.

Knowler, D. and Bradshaw, B. (2007), "Farmers' adoption of conservation agriculture: a review and synthesis of recent research", *Food Policy*, Vol. 32 No. 1, pp. 25-48.

Koihlin, G. and Amacher, G.S. (2005), "Agricultural and applied economics association welfare implications of community forest plantations in developing countries: the Orissa social forestry project", *American Journal of Agricultural Economics*, Vol. 87 No. 4, pp. 855-869.

Kuntashula, E., Chabala, L.M. and Mulenga, B.P. (2014), "Impact of minimum tillage and crop rotation as climate change adaptation strategies on farmer welfare in smallholder farming systems of Zambia", *Journal of Sustainable Development*, Vol. 7 No. 4, pp. 95-110, doi: 10.5539/jsd.v7n4p95.

Lee, L.F. (1983), "Generalized econometric models with selectivity", *Econometrica*, Vol. 51 No. 2, pp. 507-512.

Lee, J. and Nadolnyak, D. (2012), "The impacts of climate change on agricultural farm profits in the US", Paper presented at the Agricultural and Applied Economics Association's 2012 AAEA Annual Meeting, Seattle, Washington, DC, 12-14 August 2012, available at: https://ageconsearch.umn.edu/bitstream/124801/2/Lee.pdf

Lee, L.F. and Trost, R.P. (1977), "Estimation of some limited dependent variable models with application to housing demand", *Journal of Econometrics*, Vol. 8 No. 3, pp. 357-382.

Liebman, M. and Dyck, E. (1992), "Crop rotation and intercropping strategies for weed management", *Ecological Applications*, Vol. 3 No. 1, pp. 92-122.

Lin, B.B. (2011), "Resilience in agriculture through crop diversification: adaptive management for environmental change", *BioScience*, Vol. 61 No. 3, pp. 183-193.

Maddala, G.S. (1983), *Limited-Dependent and Qualitative Variables in Economics (No. 3)*, Cambridge University Press, Cambridge, p. 257-291.

Maddala, G.S. (1986), "Disequilibrium, self-selection, and switching models", *Handbook of Econometrics*, Vol. 3, pp. 1633-1688.

Maddala, G.S. and Nelson, F.D. (1975), "Switching regression models with exogenous and endogenous switching", Proceedings of the American Statistical Association, Vol. 5, *Business and Economics Section*, pp. 423-426.

Mare, R.D. and Winship, C. (1987), "Endogenous switching regression models for the causes and effects of discrete variables", *Center for Demography and Ecology*, University of WI-Madison, Madison, WI.

Maurel, M. and Kubik, Z. (2014), "Climate variability and migration: evidence from Tanzania", Working paper, No. 104, Development Policies, available at: www.ferdi.fr/sites/www.ferdi.fr/files/publication/fichiers/wp104_ferdi_maurel_et_kubik_climate_variability_and_migration_mis_en_forme.pdf

Moylan, H.G. (2012), "The impact of rainfall variability on agricultural production and household welfare in rural Malawi", Master's thesis, University of Illinois Urbana, IL, available at: www.ideals.illinois.edu/bitstream/handle/2142/34487/Moylan_Heather.pdf?sequence=1&isAllowed=y

Power, A.G. (2010), "Ecosystem services and agriculture: tradeoffs and synergies", *Philosophical Transactions of the Royal Society B: Biological Sciences*, Vol. 365 No. 1554, pp. 2959-2971.

Prasifka, P.L., Tollefson, J.J. and Rice, M.E. (2006), "Rotation-resistant corn rootworms in Iowa", Integrated Crop Management News. 1333, available at: http://lib.dr.iastate.edu/cropnews/1333

Qasim, M. (2012), *Determinants of Farm Income and Agricultural Risk Management Strategies: The Case of Rain-fed Farm Households in Pakistan's Punjab*, Vol. 3, Kassel university press, GmbH, Kassel.

Quiroga, S. and Suárez, C. (2016), "Climate change and drought effects on rural income distribution in the Mediterranean: a case study for Spain", *Natural Hazards and Earth System Sciences*, Vol. 16 No. 6, pp. 1369-1385.

Robinson, S., Willenbockel, D. and Strzepek, K. (2012), "A dynamic general equilibrium analysis of adaptation to climate change in Ethiopia", *Review of Development Economics*, Vol. 16 No. 3, pp. 489-502.

Roy, A.D. (1951), "Some thoughts on the distribution of earnings", *Oxford Economic Papers*, Vol. 3 No. 2, pp. 135-146.

Shumetie, A. and Alemayehu, M. (2017), "Effect of climate variability on crop income and indigenous adaptation strategies of households", *International Journal of Climate Change Strategies and Management*, Vol. 10 No. 4, pp. 580-595, doi: 10.1108/IJCCSM-04-2016-0039.

Silva, J.A. and Matyas, C.J. (2014), "Relating rainfall patterns to agricultural income: implications for rural development in Mozambique", *Weather, Climate, and Society*, Vol. 6 No. 2, pp. 218-237.

Snapp, S.S., Blackie, M.J., Gilbert, R.A., Bezner-Kerr, R. and Kanyama-Phiri, G.Y. (2010), "Biodiversity can support a greener revolution in Africa", *Proceedings of the National Academy of Sciences*, Vol. 107 No. 48, pp. 20840-20845.

Stanger, T.F. and Lauer, J.G. (2008), "Corn grain yield response to crop rotation and nitrogen over 35 years", *Agronomy Journal*, Vol. 100 No. 3, pp. 643-650.

Teklewold, H., Kassie, M., Shiferaw, B. and Köhlin, G. (2013), "Cropping system diversification, conservation tillage and modern seed adoption in Ethiopia: impacts on household income, agrochemical use and demand for labor", *Ecological Economics*, Vol. 93, pp. 85-93.

Tibesigwa, B., Visser, M., Hunter, L., Collinson, M. and Twine, W. (2015), "Gender differences in climate change risk, food security, and adaptation: a study of rural households' reliance on agriculture and natural resources to sustain livelihoods", Environment for development discussion paper series (EfD) 545, pp. 15-20, available at: https://econrsa.org/system/files/publications/working_papers/working_paper_545.pdf

Turkelboom, F., Thoonen, M., Jacobs, S., García-Llorente, M., Martín-López, B. and Berry, P. (2016), "Ecosystem service trade-offs and synergies", OpenNESS Ecosystem Services Reference Book. EC FP7 Grant Agreement, (308428).

United Nations (UN) (2007), "Climate change an overview", Paper prepared by the Secretariat of the United Nations Permanent Forum on Indigenous Issues, United Nations.

Woodfine, A. (2009), "Using sustainable land management practices to adapt to and mitigate climate change in Sub-Saharan Africa", *Resource Guide Version 10*, available at: www.terrafrica.org

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Appendix

Table AI. Parameter estimates of labor demand and farm income outcome model

Model	Endogenous switching regression							
	Wald Chi^2 (41) = 364.47, Log pseudo likelihood = −14166.533, Prob > Chi^2 = 0.0000							
	Labor demand for adopters		Labor demand for non-adopters		Income for adopters		Income for non-adopters	
Dependent variable	Coefficient	Robust SE	Coefficient	Robust SE	Coefficient	Robust SE	Coefficient	Robust SE
Average rainfall	−0.003*	0.001	−0.03	0.002	−0.009*	0.003	−0.01**	0.007
Average temperature	3.45***	0.47	2.58***	0.82	6.65**	2.79	5.33***	1.12
Rainfall square	0.002	0.002	0.00032	0.002	0.009	0.005	0.0001	0.008
Temperature square	−0.08***	0.01	−0.06***	0.02	−0.16**	0.07	−0.13***	0.02
CV temperature	3.91	4.98	10.87	9.98	−52.23***	13.49	−70.22**	33.34
CV rainfall	−6.29***	0.85	−7.14***	1.46	−6.44***	1.96	−8.25*	4.39
Age	0.01*	0.01	0.03**	0.01	0.06**	0.02	0.08	0.05
Age^2	−0.001	0.0001	−0.002*	0.0017	−0.006**	0.002	−0.008*	0.004
Marital status					−0.10**	0.04	−0.03	0.07
Education					−0.02	0.01	0.01	0.03
Log household size	0.10**	0.05	−0.10	0.10	−0.36**	0.16	−0.87***	0.30
Remittance					−0.17	0.14	0.02	0.27
Off farm employment	−0.17***	0.04	−0.03	0.07	−0.15	0.12	−0.25	0.21
Gender					−0.20	0.19	−0.16	0.29
Fertility index	0.17	0.19	0.30*	0.16	−0.18	0.28	0.90*	0.51
Slope index					−0.13	0.33	−0.42	0.57
Shock index	−0.12***	0.25	−0.79*	0.43	0.29	0.78	−0.25	1.45
Log plot distance	−0.01**	0.01	0.04*	0.02	−0.05	0.03	−0.05	0.07
Organic fertilizer	0.10**	0.03	0.09	0.06	0.08	0.11	0.17	0.21
Pesticide	0.09***	0.02	0.07***	0.01				
Log VPFA	0.05	0.01	0.01	0.02	−0.03	0.03	−0.05	0.06
TLU	0.03***	0.005	0.02***	0.008	−0.07***	0.02	−0.09***	0.03
Log farm size					−0.42***	0.10	−0.42*	0.16
Credit					0.20**	0.09	0.35**	0.18
Farm support					−0.27	0.19	0.03	0.30
Land tenure					0.36**	0.16	0.13	0.24
Crop dummy	Included				Included			
Zone dummy	Included				Included			
N	3,477		1,301		3,477		1,301	

Notes: ***Significant at 1% level; **significant at 5% level; *significant at 10% level