The Effect of Climate Change Adaption strategies on Household Welfare in Rural Ethiopia: A Panel Endogenous Switching Estimation

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Abstract

Climate change has had a serious effect on farm output, especially in Sub-Saharan Africa. To reduce the effect of climate change farmers require adopting mitigation strategies. Systematic use of crop rotation and improved seed is a pathway to increase farm income, but adoption of these strategies remains low. We investigate the effect of climate change on farm households' welfare in terms of farm income and explore whether the adoption of crop rotation and improved seed varieties is a strategy to increase household income. In this paper, we use household-plot level data which was collected by World Bank and Central Statistical Agency (CSA) from 2011/12 to 2015/16 from rural farm households in Ethiopia. Using the three-wave panel data, the authors estimate the maximum likelihood endogenous switching regression model (MLESM) to measure the effect of climate change adaption strategies on the farm household's welfare. The results suggest that the adoption of crop rotation and improved seed varieties helps to improve the well-being of farm households and build a resilient livelihood in rural Ethiopia. Furthermore, beyond average, we find that the effectiveness of crop rotation and improved seed is varied across farm households. Thus, policymakers should consider this heterogeneity and the adoption history of farmers when they aim to improve the practice of crop rotation and improved seed for the particular poor farmers to increase the effectiveness of the strategies.

1. Introduction

Climate change can profoundly affect the welfare of farmers in different parts of the world regions (Troost, 2014). Developing countries are extremely affected by the unprecedented climate change mainly because these countries are heavily dependent on the agricultural source of income which is highly vulnerable to the climate change effect (Fissha et al., 2019; Sam et al., 2020). More than 815 million people were undernourished in 2016, and 11% of the world's population has experienced recent decreases in food security, with higher percentages in Africa (20%), Southern Asia (14.4%), and the Caribbean (17.7%) (FAO et al., 2017). Africa is projected to lose 0.13 to 2 percent of its GDP by 2100 due to the change in climatic conditions within the agriculture sector. It is because the continent has the least capacity to adopt climate change mitigation techniques to improve the welfare of the household's i.e. irrigation, capital, farming system, technologies, and high yield varieties (IPCC, 2018). Therefore, reducing the vulnerability of agricultural systems to climate change is thus an important priority for policymakers to protect and improve the livelihoods of the poor and to maximize the welfare of the society (Bradshaw et al., 2004; Wang et al., 2008; Coromaldi, 2020).

In the last two decades, Ethiopia accounts for rigorous economic growth (World Bank, 2021). The agriculture sector bolsters approximately 80% of the population, accounts for approximately 40% of the gross domestic product (GDP), and produces almost 80% of the export earnings (USAID, 2021). However, the sector is affected by many factors related to climate change of which drought, flood, and unexpected rainfall are the major ones (Fissha et al., 2019). According to Robinson et al., (2012) the temperature is forecasted to increase 1.7 to 2.7^0c in the year 2050 which is highly disastrous. If it will be the case, households are still prone to risks and external shocks that cause them to slip back into poverty or remain in it, particularly if they are near the poverty line. Household incomes also fluctuate strongly due to climate variability and other shocks since there is very limited scope for insurance, household consumption and poverty vary considerably over time (Fabrizi and Mussida, 2020). In the literature, climate change adaption can minimize the effect of climate change on household welfare (see Skoufias, 2012; Seaman et al, 2014; Hailu et al., 2021; Fissha et al., 2019; Sam et al., 2020). However, the adaption of climate change is very low in Ethiopia (Berger et al., 2017). In the area where this study is conducted, agriculture is rain-fed in which only 2.2 percent of the households are irrigators.

In this paper, we consider rainfall and temperature as climate change measures. In our data set farmers face damage to their crops from too little rain, too much rain, flood, spoiled seed, crop disease, and others. As an adaption strategy crop rotation is a good attempt to manage 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, crop rotation serves as a hedge against the extreme or unseasonal temperatures, rainfall variations, and risk of drought, and price fluctuations that affect the productivity and income of smallholder farmers (Fissha et al., 2019). Accordingly, several studies provide empirical evidence on the contribution of crop rotation to farmers. Campbell et al., (1991), Liebman and Dyck (1992); Azevedo et al., (1999); and Stanger and Lauer, (2008) found that crop rotation can improve crop yield significantly. This is attributed to the large amount of Nitrogen concentration existence under different rotation sequences. It also has vital importance in controlling pests, weeds, insects, and crop diseases (Prasifka et al., 2006; Cavigelli et al., 2013). Even though studies (Tibesigwa et al., 2015; Afolami et al., 2015; Kuntashula et al., 2014; Bola et al., 2012; Hailu et al., 2021, and Asfaw, 2010) showed climate change adaptation measures like crop rotation, irrigation, and improved seed variety can improve households' welfare, their effort has been questioned when we consider dynamics.

The literature on the welfare effect of climate change is large and varied. Most of the literature establishes a negative relationship between income and climate change in general and positive linkages between income and rainfall in developing and Sub Saharan African countries (Winters et al., 1996; Nordhaus and Yang, 1996; Deke et al., 2001; Dell et al., 2014; Miguel et al., 2004; Dercon et al., 2005; Guiteras, 2009; Barrios et al., 2010; Feng et al., 2010; Schlenker et al., 2010; Welch et al., 2010; Hsiang, 2010; Brückner et al., 2011; Sam, 2020; Coromaldi, 2020). However, Yates and Strzepek, 1998 found that the insignificant effect of climate change on welfare was measured by the sum of consumer and producer surplus in Egyptian agriculture. Narloch et al., (2018) found that there is no causation between the environmental risks and poverty in Vietnam.

In the case of Ethiopia, Fissha et al., (2019) used data from 929 rural farm households collected in 2015, confirms a positive and significant effect on farm income and suggest that adoption of crop diversification helps improve the well-being of farm households. Using cross-sectional data, Hailu et al., (2021) found that the adoption of multiple combinations of improved technologies rather than in isolation has substantial effects that improve the food security status of smallholders in rural Ethiopia. Deressa, (2007) also examines the impact of climate changes on net revenue per hectare using different models with scenarios. The data was collected from different agro-ecological zones covering 1,000 farmers from 50 districts. The result proved that climate has a significant impact on the farmers' net revenue per hectare. The predicted climate scenarios show a positive net revenue impact for the year 2050 but a negative one for the year 2100. In addition, increasing temperature and decreasing precipitation are both damaging to Ethiopian agriculture. However, these studies did not consider the time effect of adaption practices.

Thus, in this paper, we analyze the effect of climate change on rural farm households' welfare by considering farm income as measures of welfare and time under consideration. Specifically, we examine the differential effect of climate variables and other socio-economic factors on farm income among adopters and non-adopters of climate change adaptation strategies; we explore the average adoption effect of crop rotation and improved seed varieties on farm income, and we show whether adoption of these climate change adaption strategies is effective in terms of effects on farm income. Therefore, the contribution of this paper will be threefold. First, it will investigate the impact of climate change adaption strategies on household welfare in rural households using an empirical framework grounded on economic theory. Second, it uses the three waves of the Ethiopia Socioeconomic Survey (ESS) panel data to analyze the welfare effect of climate change among rural households. Thus, it will show the time effect of practicing climate adaption strategies in which cross-sectional data cannot. Lastly, our analysis will provide important insights for targeted policy interventions such as social protection services for poor smallholder farmers to the effects of climate change based on the adoption history of farmers and expected adoption benefit.

The remaining section of the paper is structured as follows. In section 2 data used is presented. Section 3 explores empirical strategy. Section 4 discusses the main findings and results of the study. Finally, Section 5 concludes.

2. The Data set

In this paper, we used the Ethiopian Socioeconomic Survey (ESS) panel data, a nationally representative survey with a strong focus on agriculture and household well-being. The ESS was collected in a collaborative effort of the World Bank's Living Standards Measurement Study Integrated Surveys of Agriculture program (LSMISA) and the Central Statistical Agency of Ethiopia (CSA). The ESS collects detailed information on agricultural practice, household characteristics, household income, plot characteristics, credit, adaptation practices, climatic conditions and environmental effects faced by households, household consumption, and food security. Households were interviewed in three rounds from 2011/12 to 2015/16, with data collected at multiple levels including region, community, household, plot, parcel, and crop. The ESS began in 2011/12 with 3776 rural and small-town households. Of these, the second wave and the third wave successfully re-interviewed 3699 households. This implies a panel attrition rate of 2% or a successful follow-up rate of 98%. The ESS used a stratified two-stage sampling design, where the regions of Ethiopia served as the strata from which enumeration areas (EAs) were selected proportionally based on regional population size. In this study we used 1588 households to construct our panel data set. We also collect rainfall and temperature data from the Ethiopian meteorology Agency.

The descriptive statistics of our main outcome and explanatory variables are provided in Appendix I, by the adaption status of the farm households. The outcome variable, farm income is higher for adopters than non-adopters for both climate change adaption strategies (CR and IS) but highly significant for IS. The figures for climate variables show a substantial difference between adopter and non-adopter households in both adaption strategies considered. Specifically, adopters of CR get more average rainfall and average temperature significantly during the survey rounds. In contrast, the mean difference is insignificant for adopters of improved seeds. Figures for rainfall variability and temperature variability show similar patterns in the case of CR but not for IS. Specifically, there is a significant difference between adopters and non-adopters in both adaption strategies. Temperature variability is significantly higher for non-adopters of CR and IS. Rainfall variability is relatively high for non-adopters of crop rotation and relatively low for adopters of IS.

There is a higher significant difference of Shared labor, year of schooling, number of the crop, and plot size for non-adopters than adopters of CR significantly. Herbicide, land certificate, extension service, and credit service are of higher significance for adopters than non-adopters of CR. There is also a significant mean difference between adopters and non-adopter of IS for those who used fertilizer and fungicide. There is not much significant difference between adopters and non-adopters of CR and IS as far as pesticide use, plot slope, hired labor, fungicide use, head age, household size, and head Sex are concerned (see Appendix I). But, we can not make any observations regarding the causality that links the climate change adaption strategies to these differences without considering for potentially confounding factors.

3. Empirical Approach

Climate change adaption strategies can be modeled under the random utility theory which says that farmers will choose between adoption and non-adoption based on the utility they will receive. It is assumed that farmers adopt climate change strategies if they expect the utility from adoption is greater than non-adoption. Farmers are therefore assumed to choose the strategy that will provide them the maximum benefits (Abdulai & Huffman, 2014). Considering a generalized panel data switching regression model with correlated unobserved effects, under the assumptions that, the utility (yield/income) farmers derive from the adoption of climate change strategies is regime 1, and the utility from non-adoption represented as regime 2, the net income of two regimes (represented by y_{it}^{r}) as a function of explanatory variables can be specified in a panel form as:

$$y_{it}^{r} = x_{it}^{r}\beta^{r} + \alpha_{i}^{r} + u_{it}^{r} \quad \text{if } \Delta\iota\tau = \rho \quad ; \iota=1; :::;N; \tau = 1; :::; T; \rho=1;2 \qquad (3.1)$$[1]

$$D_{it}^{r*} = w_{it}^{r}\gamma_{t}^{r} + \varphi_{i}^{r} + v_{it}^{r} \quad ;\iota =1; :::;N; \tau =1; :::; T; \rho =1;2 \qquad (3.2)$$

Where x_{it}^{r} and w_{it}^{r} are $1xK_r$ and $1xL_r$ vectors of exogenous covariates (which may overlap) with corresponding conformable parameter vectors β^{r} and γ_{t}^{r}. α_{i}^{r} *and* φ_{i}^{r} are individual-specific unobserved effects that are allowed to be correlated with right-hand-side covariates. The outcome variable y_{it}^{r} it is observed only if the r[th] regime is selected. The regime selection (switching) is governed by a latent variable D_{it}^{r*} with observable categorical realizations: $D_{it} = r$ if the r[th] regime is selected which is either to adopt or not to adopt. While the disturbances $u_{it}^{r}$and v_{it}^{r} are orthogonal to (x_{it}^{r}, w_{it}^{r}), their distributions are however allowed to be correlated, namely $E[u_{it}^{r}v_{it}^{r}|x_{it}^{r}, w_{it}^{r}] \neq 0$ (Malikov and Kumbhakar, 2014; Lokshin and Sajai, 2004). Let us assume that $u_{1it}, u_{2it}, and\ v_{it}$ have a trivariate normal distribution with mean vector zero and covariance matrix

$$\Omega = \begin{bmatrix} \delta_u^2 & \delta_{1u} & \delta_{2u} \\ \delta_{1u} & \delta_1^2 & . \\ \delta_{2u} & . & \delta_2^2 \end{bmatrix}$$

Where δ_u^2 is a variance of the error term in the selection equation, and δ_1^2 and δ_2^2 are variances of the error terms in the continuous equations. δ_{1u} is a covariance of v_{it} and u_{1it}, and δ_{2u} is a covariance of v_i and u_{2i}. The covariance between u_{1i} *and* v_{2i} is not defined as y_{1it} and y_{2it} are never observed simultaneously. We can assume that $\delta_u^2 = 1$ (γ is estimable only up to a scalar factor). The model is identified by construction through nonlinearities. Given the assumption to the distribution of the disturbance terms, the logarithmic likelihood function for the system is

[1] This implies that, the two regimes are

Regime 1: $y_{it}^{1} = x_{it}^{1}\beta^{1} + \alpha_{i}^{1} + u_{it}^{1}$ if D_{it}=1 (given D_{it}=1 if $w_{it}^{r}\gamma_{t}^{r} + \varphi_{i}^{r} + v_{it}^{r} > 0$)

Regime 2: $y_{it}^{2} = x_{it}^{2}\beta^{2} + \alpha_{i}^{2} + u_{it}^{2}$ if D_{it}=2 (given D_{it}=1 if $w_{it}^{r}\gamma_{t}^{r} + \varphi_{i}^{r} + v_{it}^{r} \leq 0$)

$$\boldsymbol{lnL} = \sum_{i} (\boldsymbol{D_{it}\omega_{it}}\,[\boldsymbol{ln}\{\boldsymbol{F}(\boldsymbol{\vartheta_{1it}})\} + \boldsymbol{ln}\{\boldsymbol{f}(u_{1it}/\sigma_1)/\sigma_1\}] + (\boldsymbol{1} - \boldsymbol{D_{it}})\boldsymbol{\omega_{it}}[\boldsymbol{ln}\{\boldsymbol{1} - \boldsymbol{F}(\boldsymbol{\vartheta_{2it}})\} + \boldsymbol{ln}\{\boldsymbol{f}(u_{2it}/\sigma_2)/\sigma_2\}]) \quad (3.3)$$

Where F is a cumulative normal distribution function, f is a normal density distribution function, ω_{it} is an optional weight for observation i at time t. After estimating the model's parameters, the following four conditional expectations will be calculated in our model estimation to estimate the average treatment effects and the counter-factual case, that is, when households that had adopted CR or IS did not adopt, and when households that had not adopted the strategies did adopt.

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

$$E(y_{1it}/D_{it} = 1, x_{1it}) = x_{1it}\beta_1 + \delta_1\rho_1 f(\gamma Z_{it})/\mathrm{F}(\gamma Z_{it}) \quad (3.4)$$

Case 2: Non-adopters without adoption:

$$E(y_{1it}/D_i = 0, x_{1it}) = x_{1it}\beta_1 - \delta_1\rho_1 f(\gamma Z_{it})/\{1 - \{\mathrm{F}(\gamma Z_{it})\} \quad (3.5)$$

Case 3: Adopters had decided not to adopt:

$$E(y_{2it}/D_{it} = 0, x_{2it}) = x_{2it}\beta_2 - \delta_2\rho_2 f(\gamma Z_{it})/\{1 - \{\mathrm{F}(\gamma Z_{it})\} \quad (3.6)$$

Case 4: Non-adopters had decided to adopt:

$$E(y_{2it}/D_{it} = 1, x_{2it}) = x_{2it}\beta_2 + \delta_2\rho_2 f(\gamma Z_{it})/\mathrm{F}(\gamma Z_{it}) \quad (3.7)$$

Having calculated the conditional expectations, then we can estimate the treatment effect for adoption and non-adoption.

The treatment effect for adoption (TT)= $E(y_{1it}/D_{it} = 1, x_{1it}) - E(y_{2it}/D_{it} = 1, x_{2it})$ (3.8)

The treatment effect for non-adoption (TU)=$E(y_{1it}/D_i = 0, x_{1it}) - E(y_{2it}/D_{it} = 0, x_{2it})$ (3.9)

If we subtract equation 3.9 (TU) from Equation 3.8 (TT), we get the transitional heterogeneity (TH) which shows whether the effect of adopting climate change adaption strategies (CR or IS) is smaller or larger for the adopters compared to the non-adopters.

4. Results and Discussions

4.1. Determinants of Farm Household's Welfare and Adaption Decision

To assess the effects of climate change, we ran ESRM using the Full Information Maximum likelihood (FIML) estimation technique. We found that climate change has an adverse effect on household farm incomes for non-adopters; rainfall has a non-linear and insignificant effect on household farm incomes for non-adopters. However, Rainfall has a positive and significant effect on household farm income for adopters of crop rotation (CR). And Temperature has a negative and significant effect on adopters of CR. A unit's increase in rainfall increases the income of adopters by 0.0029 unit and decrease the income of non-adopters by 0.0039 units. This is because the non-adopters farm income is compromised by the effect of rainfall variability. On the contrary, adopters of crop rotation become beneficiaries since crop rotation reduces the effect of rainfall variability on crop yield by changing the decision of farmers to adopt or not to adopt. Moreover, crop rotation increases agricultural resilience to adverse growing conditions (Bowles et al., 2020).

Table 4.1: ESRM Estimation Results (CR)

	Endogenous switching regression		
Dependent variable	Income for CR adopters	Income for non-adopters	CR Adaption
Average rainfall	0.00294***	-0.00392	0.00788***
	(0.000752)	(0.00324)	(0.00119)
Rainfall square	-1.06e-06***	1.51e-06	-2.85e-06***
	2.6 e-07	(1.28e-06)	(4.55e-07)
Average temperature	-0.0394**	0.228**	-0.0701***
	(0.0163)	(0.0955)	(0.0218)
CV temperature	-34.81***	100.0**	-138.3***
	(8.592)	(43.15)	(14.24)
CV rainfall	3.068***	-1.386	3.905***
	(0.690)	(2.131)	(0.797)
Total fertilizer	0.00944***	0.0222	0.00124
	(0.00242)	(0.0155)	(0.00144)
Household Labor	0.0184***	0.0197**	0.00325
	(0.00331)	(0.00770)	(0.00294)
Hired Labor	-0.000720	0.00449	0.000680
	(0.00118)	(0.0144)	(0.000464)
Shared Labor	0.0149**	0.0442***	0.00272
	(0.00670)	(0.0130)	(0.00835)
Plot Size	9.71e-05**	3.72e-05***	-1.33e-05**
	(4.95e-05)	(1.26e-05)	(6.49e-06)
Number of crops	-0.521***	-0.205	-0.553***
	(0.143)	(0.156)	(0.0901)
Household size	0.0199	0.0723	0.0303
	(0.0176)	(0.0698)	(0.0235)
Head Sex	0.0694	-0.505	0.174
	(0.0991)	(0.332)	(0.150)
Head Age	-0.00105	-0.00767	0.00203
	(0.00231)	(0.00792)	(0.00351)

Plot Slope	-0.185*	-0.147	0.0843
	(0.108)	(0.456)	(0.180)
Soil Quality	0.143*	0.585**	0.116
	(0.0830)	(0.254)	(0.126)
Extension Service	0.0467	-0.0421	0.434***
	(0.0748)	(0.286)	(0.108)
Pesticide	0.156	0.999	-0.160
	(0.218)	(0.806)	(0.294)
Herbicide	0.325***	1.426***	0.266
	(0.116)	(0.474)	(0.227)
Land certificate			0.182*
			(0.104)
Constant	2.720***	-1.189	-0.713
	(0.692)	(2.722)	(0.887)
Observations=1588			
Wald chi2(19) = 71.01			
log pseudo likelihood = -3074.2309			
Prob > Chi^2 = 0.000			

Notes: ***Significant at 1% level; **significant at 5% level; *significant at 10% level; Robust standard errors in parentheses

The results of the farm income regression for adopters are reported in column 2 of Table 4.1, and the income regression for non-adopters is reported in the third column. The last column displays the determinates of household adaption selection to adopt or not to adopt CR. Explanatpry varables are jointly significant as shown by Wald chi2(19) = 71.01 at Prob > Chi^2 = 0.000, In our regression (not reported here), the correlation coefficients rho 0 and rho 1 are both significant but are positive only for the correlation between the climate change adaption choice equation and the non-adapter farm income equation. Since rho 1 is positive and significantly different from zero, the model suggests that individuals who choose to not adopt crop rotation earn lower income in that sector than a random individual from the sample would have earned, and those who adopt crop rotation do no better or worse than a random individual. The likelihood-ratio test for joint independence of the three equations is significant (Wald test of indep. eqns.: chi2(2) = 16.01 with a Prob > chi2 = 0.0003).

The the negative sign of rainfall square shows that as rainfall increases income tends to decline for CR adopters after a certain point. However, rainfall square has a positive and significant impact on non-adopters. This result confirms that adopting crop rotation has an advantage when rainfall is low. This implies the effect of climate change can be reduced by adoption of CR. This result is also supported by many empirical evidences in the world in which climate change affect farm income adeversily. For instance, Bobojonov and Aw-Hassan. (2014) indicated that in the central Asia an increase in temperature boosts farm revenue initially, it has a negative effect after some point. Lee and Nadolnyak, (2012) (2014) also found a similar result for USA in which climate change affect the farm profit negatively when farmers join the highly drier climate scenario. Moreover, Quiroga and Suárez, (2016) reported that tremendous increament in temperature and lower precipitation also negatively affect agricultural farm income and income distribution in Spain. Studies in Ethiopia also shows similar result (Deressa, 2007; Aragie, 2013; Fissha et al., 2019;

Gebreegziabher et al., 2011). On the other hand, an increase in average increases the income of farm households for adopters and decrease the income of non-adopters.

Furtheremore, rainfall and temperature variability are crucial factors that affect farm households' income in rural Ethiopia. This suggests that even if the total amount of rain during a given production year is enough, its timing and distribution are vital. Thus, giving attention to variability is very important. Household farm income is highly and significantly affected by rainfall and temperature variability for both adopters and non-adopters. When the variability of rainfall increases the income of adopters will increase but decline for non-adopters. Unlike our results Shumetie and Alemayehu (2017) and Fissha et al. (2019) found that rainfall variability in the cropping season has a significant negative effect on farm income for adopters. Two related implications of our results are: first, in addition to average rainfall and temperature, attention should be paid to their variability; second, CR 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 the high temperature and extraordinary rainfall variability. Moreover, other socio-economic and farm-related factors are found to be significant determinants of farm household welfare. Factors with negative and significant effects on farm household income adopters and non-adopters are head age, plot slope, and the number of crops. On the contrary, from the variables incorporated in this study, total fertilizer, household labor, shared labor, plot size, soil quality, and herbicide are found positive and significant determinants of farm household income of adopters and non-adopters. However, Qasim, (2012) reported the opposite result regarding land size in which he revealed that higher land size is associated with reduced farm income in Pakistan and Malawi respectively.

Adaption selection to CR: As shown in column 4 of Table 4.1, the effect of rainfall and temperature on adaption to crop rotation is found non-linear and significant for both adopters and non-adopters. Initially, rainfall has a positive impact but after some point, it exhibits an inverse relationship. This is because when the rainfall increases farmers will take different measures to hedge from the effect of high rainfall or flood like terracing, and soil conservation activities. And the temperature has a negative impact. Farmers will search non-farm and off-farm emplotment opportunities when the effect of temperature becomes overwhelming (Fissha et al., 2019). In addition to this, temperature variability is also found to be a negative and significant determinant for the adaption of CR. The effect extension service and land certificate have positive and significant as can be seen from the results in Table 4.1 of column 4. Other control variables such as plot size and the number of the crop have a negative and significant effect on farm household adaption selection of crop rotation.

Table 4.2: ESRM Estimation Results (IS)

Endogenous switching regression

Dependent variable	Income for IS adopters	Income for non-adopters	IS Adaption
Average rainfall	0.00316***	0.00214**	0.00699***
	(0.00120)	(0.00101)	(0.000846)
Rainfall square	-1.14e-06***	-7.72e-07**	-2.38e-06***
	(4.27e-07)	(3.75e-07)	(3.13e-07)
Average temperature	0.00557	-0.0455**	0.0464***
	(0.0235)	(0.0214)	(0.0167)
CV temperature	-20.03*	-21.08	7.821***
	(11.77)	(13.28)	(0.488)
CV rainfall	3.820***	3.121***	-57.26***
	(1.245)	(0.847)	(5.458)
Total fertilizer	0.0122***	0.00772**	0.00635***
	(0.00224)	(0.00324)	(0.00240)
Household Labor	0.0206***	0.0180***	0.000800
	(0.00403)	(0.00414)	(0.00249)
Hired Labor	0.00268	-0.000536	-0.000551
	(0.00320)	(0.000834)	(0.000360)
Shared Labor	0.0132*	0.0230**	0.00439
	(0.00777)	(0.0111)	(0.00580)
Plot Size	6.15e-05	7.24e-05**	2.26e-06
	(4.79e-05)	(3.64e-05)	(9.00e-06)
Number of crops	-0.203	-0.446***	0.353***
	(0.136)	(0.126)	(0.0947)
Household size	0.0284	0.0212	0.0256
	(0.0239)	(0.0237)	(0.0182)
Head Sex	0.118	0.00740	-0.0657
	(0.149)	(0.135)	(0.113)
Head Age	-0.00210	-0.00228	-0.00711***
	(0.00333)	(0.00310)	(0.00269)
Plot Slope	-0.107	-0.247*	0.142
	(0.159)	(0.145)	(0.120)
Soil Quality	0.254**	0.155	0.784***
	(0.113)	(0.120)	(0.0882)
Extension Service	0.129	-0.0695	0.257***
	(0.107)	(0.104)	(0.0841)
Pesticide	0.321	0.00198	-0.194
	(0.312)	(0.256)	(0.237)
Herbicide	0.357***	0.422**	0.00659
	(0.474)	(0.116)	(0.227)
Credit Services			-0.309***
			(0.0879)
Irrigation			0.374
			(0.315)
Years of Schooling			0.0145*

			(0.00761)
Advisory Service			-0.155
			(0.101)
Constant	0.799	3.298***	-7.203***
	(1.283)	(0.843)	(0.794)

Observations=1586
Wald chi2(19) = 121.48
log pseudo likelihood = -3468.8988
Prob > Chi^2 = 0.000

Notes: ***Significant at 1% level; **significant at 5% level; *significant at 10% level; Robust standard errors in parentheses

Table 4.2 presents the determinant of farm income for adopters and non-adopter of improved seed in columns 2 and 3 respectively. The fourth column indicates the adaption selection estimates to adopt or not to adopt IS. Column 1 looks at the factors that affect farm household income for adopters of IS. A negative effect of high rainfall as shown by rainfall squared and high-temperature variability would suggest that climate change has a discouraging impact on adopters of IS. However, average rainfall and rainfall variability have a positive and significant effect on adopters of IS. There is a weak positive effect of average temperature implying that improved seed may improve agricultural production. This may be because the seed needs optimum temperature to achieve a required level of agricultural production. In contrast to Adopters, the temperature is negatively associated with farm household welfare for non-adopters (column (3)). Our results are consistent with Tibesigwa et al., (2015); Afolami et al., (2015); Kuntashula et al., (2014); Bola et al., (2012); Hailu et al., (2021), and Asfaw, (2010).

There is also a larger and more significant positive effect of fertilizer for both adopters and non-adopters on farm household income in columns (2) and (3). Moreover, for Adopter and non-adopters in columns (2) and (3) respectively, we get high levels of family household workers and shared labor which has a positive impact on farm income. Other control variables such as soil quality and herbicide were found to have a positive significant effect for both adopters and non-adopters. Plot slope and the number of crops are negative significant effects for non-adopters but insignificant for adopters of IS. Column (4) shows that all climate variables have a significant effect on the adaption decision of IS. Moreover, fertilizer, number of crops, soil quality, extension service, and household education level which is measured by year of schooling have a positive and significant effect to adopt IS. In contrast, the age of the household head and credit services have a significant negative effect to adopt IS.

Therefore, our results make sense. Climate change is affecting both adopters and non-adopter in one way or another but adopters can resist more than non-adopters for both IS and CR. Thus, adopting CR and IS are the main instrument in adopting climate change variability. The battle cry of climate change is often that climate change adaption strategies such as CR and IS redress the unfavorable agricultural outcomes, leading to a progressive effect on welfare. Thus, the adoption of crop rotation and improved seed provide proven benefits to farmers' food security, resilience, and productivity in the channel of farm income improvement.

4.2 Average adoption effect of Crop Rotation and Improved Seed

Table 4.3 presents the average effect of the adoption of CR on farm income. The number in the first row and first column of Table 4.3 is the average income value ($151.4) for adopters of CR. The number in the second column of the first row ($130) 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 ($40***). The result is positive and significantly different from zero which suggests that the farm household's income for those who adopted CR is significantly higher than if they did not adopt. By using a similar procedure, the adoption effect of CR on non-adopters can be calculated from Table 4.2. In the second row and first column of Table 4.2, 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 ($80 ***). The result indicates that net farm income will increase significantly if they adopt CR than the actual case of non-adoption. Asfaw (2010), Bola et al. (2012), Tibesigwa et al. (2015), Bradshaw et al., (2004), Bhattacharyya, (2008), Di Falco et al., (2011), and Kuntashula et al., (2014) and Afolami et al. (2015) indicated that climate change adaptation measures like CR improve household's welfare.

Table 4.3: Adoption Effects of CR and IS on growth of farm income

			Decision		
	(1)	(2)	(3)	(4)	(5)
			Adopter	Non-Adopter	Adoption effect
(1)	Crop rotation	Adopter	4.154204 (0.6754)	3.392008 (0.8620)	TT=0.762196
(2)		Non-adopter	3.957161 (0.7546)	2.507525 (1.2921)	TU=1.449591
					TH=0.687395
(3)	Improved seed	Adopter	4.29495 (0.0341)	3.302243 (0.0571)	TT=0.992707
(4)		Non-adopter	4.028184 (0.0836)	2.537388 (0.0577)	TU=1.490796
					TH=-0.498089

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

Table 4.3 presents the average effect of the adoption of CR and IS on the growth of farm income. The number in the first row and third column of Table 4.3 is the average income growth value

(4.154204) for adopters of CR. The number in the fourth column of the first row (3.392008) indicates the average growth of net farm income for adopters of CR in the counterfactual case. So, the adoption effect on adopters can be found by subtracting the second from the first (0.762196). The result is positive and significantly different from zero which suggests that the growth of farm household’s income for those who adopted CR is significantly higher than if they did not adopt. By using a similar procedure, the adoption effect of CR on non-adopters can be calculated from Table 4.3. In the second row and third column of Table 4.3, we find the value of the growth of farm income for non-adopters in the counterfactual case, while the fourth column in the second row represents the same value in the actual case. Thus, the difference between these two cells of the second row gives us the growth of farm income of non-adopters (1.449591). The result indicates that net farm income will increase significantly if they adopt CR than the actual case of non-adoption. Studies like Fissha et al., (2019), Di Falco et al., (2011); Tibesigwa et al., (2015); Kuntashula et al., (2014); Afolami et al., (2015) showed that climate change adaptation measures like CR improve household’s welfare.

By following the same procedure as the one for CR analysis we did above, the average expected farm income growth in the actual and counterfactual case is estimated for both adopters and non-adopters of improved seed. This estimation helps to know specifically the treatment effect on adopters (TT), treatment effect on non-adopters (TU), and also the transitional heterogeneity (TH). The number in the third row and third column of Table 4.3 is the average farm income growth (4.29495) for adopters of IS. The number in the fourth column of the third row (3.302243) indicates the average household income growth for adopters had they been non-adopters. Then the adoption effect on IS adopters can be found by subtracting the second from the first (0.992707). The result is positive and significantly different from zero. This indicates that farm households can increase their income by 0.992707 by adopting IS. By using a similar procedure, the adoption effect of IS on non-adopters farm income can be calculated from Table 4.3. In the fourth row and third column of Table 4.3, we find farm households’ income for non-adopters in the counterfactual case, while the fourth column in the fourth row shows the value in the actual case. Thus, the difference between these two columns of the fourth row gives farm household income of non-adopters of IS (1.490796). The result shows that non-adopter farm households can get an advantage of increasing farm income by 1.490796 if they adopt improved seeds. This is in line with the works of Hailu et al., (2021). Finally, the last cell in the fifth column gives the value for TH. This value is negative and significantly different from zero (-0.498089) implying by adopting IS adopters benefit more than the non-adopters, albeit both are beneficiaries from adoption.

5. Conclusions

This paper has examined the link between climate change and household welfare using Ethiopian socioeconomic survey (ESS) panel data ranging from 2011/12 to 2015/16. We employed a panel endogenous switching regression model (ESRM) in a full maximum likelihood estimation setting to estimate the adoption of crop rotation and improved seed effect on farm income with its determinant 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 estimation results of the study. First, the evidence amassed in the paper points to the adaption of crop rotation and improved seed as key strategies in the pattern of welfare improvement among smallholder farmers. Second, it was found that climate variables such as temperature and rainfall, and application of technologies such as fertilizer and herbicide are the main determinants of farm household welfare. Farm income of adopters is positively determined by rainfall and negatively by temperature. However, the income of non-adopters is negatively determined by rainfall and positively by temperature for adopters of CR. Thus, it is very important to work on the promotion and expansion of CR through the provision of extension services to better use CR as a hedge for higher temperatures. In addition, head age, plot slope, and the number of crops are found negative determinants of farm income. And other variables such as total fertilizer, household labor, shared labor, plot size, soil quality, and herbicide are found positive and significant determinants of farm household income of adopters and non-adopters of CR.

Adaption of CR is found to be determined by average rainfall and rainfall variability positively and significantly. However, rainfall squared has a negative impact on adaption selection. Average temperature and temperature variability affect the household decision to adopt or not adopt crop rotation negatively. Third, for both adopters and non-adopters of CR, the strategy can improve farm households' welfare if they decided to adopt than they would if they had not adopted. Surprisingly, non-adopters CR can get a greater payoff compared to adopters if both of the two groups decided to adopt as shown in the average treatment effect result. This is also true for both groups in the case of IS adaption. Fifth, the average treatment effect of adopting improved seed on-farm income use is also significant for both adopters and non-adopters had they been adopters. Furthermore, climate variables are found to be the significant determinant of the adoption of IS.

Finally, the adoption of CR and IS provides a double benefit for both adopters and non-adopters. For both groups, it can increase the well-being of farm households through an increase in welfare. The analysis reinforces the growing sentiment that adaption of climate change strategies has promoted farm household welfare and extension and advisory workers should participate in the promotion and improving households knowledge regarding CR and IS. However, the extent of the treatment effect in both adoption of CR and IS are different. This shows the heterogeneity found between adopters and non-adopters. Therefore, policymakers should consider this heterogeneity to accelerate the advancement of CR and IS to a maximum effort in achieving better wellbeing of farm households in rural Ethiopia.

Consent for publications

The authors confirm that the content of the manuscript has not been published, or submitted for publication elsewhere.

Availability of data and materials

The datasets and Stata do-files are available from the corresponding author upon reasonable request.

Conflict of interest

The author(s) declared no potential competing interest in the research, authorship, and/or publication of this article.

Author's Contribution

The research idea was originally thought by YKM. The authors searched for the existing literature together. They equally contributed together in specifying the empirical models and analyzing the econometric results. They also discussed the results, wrote up the manuscript, and revised the paper. All authors read and approved the final manuscript.

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Appendix

Appendix I: Description and summary statistics of variables

	Crop Rotation					Improved Seed				
	Adopter		Non-Adopter		Mean Diff	Adopter		Non-Adopter		Mean Diff
VARIABLES	Mean	SD	mean	SD		Mean	SD	Mean	SD	
Farm income	152.383	252.96	144.23	242.51	-8.1531	178.601	292.617	134.5212	220.809	-44.08***
Averagerainfall	1207.38	420.23	907.43	323.19	-299.96***	1178.82	416.34	1165.277	424.13	-13.55
Rainfall square	1634252	1073859	927330	769958	-706922***	1562689	1044133	1537575	1080981	-25113.9
A.temperature	19.97773	0.06261	21.295	0.1349	1.3171***	20.11704	0.09603	20.15295	2.3757	0.03591
Temperature ^{2}	404.5774	96.246	456.94	80.737	52.362***	410.3302	98.261	411.42	94.666	1.0857
CV rainfall	0.26138	0.00308	0.3068	0.1253	0.04546***	0.3147	0.11506	0.23689	0.108317	-0.0778***
CVtemperature	0.01642	0.00642	0.0233	0.0078	0.00691***	0.0153	0.00654	0.01849	0.0069	0.00323***
Fertilizer	8.59722	26.322	5.5704	12.418	-3.0268	12.0531	29.384	5.836493	21.6354	-6.2166***
Pesticide	0.030086	0170885	0.0208	0.14319	-0.0092526	0.02451	0.154752	0.031827	0.175631	0.00731
Herbicide	0.12106	0.32631	0.03125	0.17444	-0.0898***	0.11111	0.314527	0.109856	0.312871	-0.001255
Fungicide	0.007163	0.08436	0.000	0.0000	-.0071633	0.0000	0.0000	0.0102669	0.100856	0.01026***
Land Certificate	0.647564	0.477899	0.32812	0.47076	-0.31944***	0.596405	0.491019	0.61704	0.48636	0.0206379
Num of plots	2.282951	2.522051	2.0416	1.8946	-.2412846	2.581699	2.829849	2.0451	2.1648	-.5365***
Plot Size	1863.947	3284.777	2403.5	7157.7	1929.18**	2022.64	3928.473	1873.473	3984.061	-149.167
Num of crops	1.070917	0.309907	1.4531	0.8237	0.3822***	1.132353	.454617	1.107803	.4076361	-0.02455
Household size	5.762894	2.045444	5.8545	1.8978	0.09127	5.830065	2.045444	5.737166	2.08866	-0.0929
Head Sex	0.872493	0.333659	0.86979	0.33741	-0.002701	0.872549	0.33375	0.87268	0.3335	0.00014
HH Age	48.87828	14.50714	47.695	14.576	-1.182971	47.80365	14.41842	49.3098	14.54917	1.5061**
HH Labor	11.9134	14.94329	12.35677	12.53404	.4433575	12.73754	15.11971	11.49538	14.38038	-1.24216
shared Labor	1.54011	6.460065	2.578125	6.726064	1.03801**	1.779412	5.513741	1.597536	7.056244	-0.18187
Hired Labor	3.673352	62.86689	2.239583	10.02222	-1.433769	2.369281	16.4985	4.217659	74.25749	1.84837
Schooling (yr)	1.817335	3.556449	2.588542	10.07784	0.771206**	2.075163	5.242178	1.811088	4.569801	-0.264075
Plot Slope	0.103152	0.304266	0.08854	0.28482	-0.01461	0.099673	0.299808	0.102669	0.303683	0.0029
Soil Quality	0.217048	0.412384	0.2187	0.41447	0.0017013	0.295752	0.456753	0.167351	0.373481	-0.128***
Extension service	0.523639	0.499619	0.3281	0.47075	-0.1955***	0.555556	0.497311	0.465092	0.499036	-0.091***
Credit Service	0.280802	0.449552	0.09895	0.29938	-0.1818***	0.266339	0.442406	0.253593	0.4352911	-0.01274

Number of Observations=1588

Notes: Average rainfall is the mean annual rainfall which is measured by mm. The average temperature is the mean annual temperature expressed as a unit of degrees Celsius (^{0}c). CV rainfall and CV temperature is Coefficient of variation in rainfall and temperature respectively. Total Fertilizer is the total amount of fertilizer application in kg on the plot. Pesticide, Fungicide, Herbicide, land certificate, and credit service are dummy variables expressed as 1=If the household use, have applied or received and 0, otherwise. Plot slope and soil quality are also dummy variables expressed as 1=If the plot are sloppy and the soil is good respectively and 0, otherwise. Plot size is the size of the plot measured using GPS, in hectare. Household labor is labor from the family of the given household per person per day. Shared labor is the shared labor from other households per person per day, and hired labor is the number of workers employed in the plot for the given household.