

The effects of climate change adaptation strategies on the welfare of rural farm households in Ethiopia

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Abstract

We estimate the effect of multiple climate change adaptation strategies (CCAS) on farm household welfare using a new three-wave panel data derived from the World Bank's geo-referenced household socioeconomic survey and the National Aeronautics and Space Administration's (NASA) historical weather data. Using the multinomial panel endogenous switching regression model, we discovered that combining climate change adaptation strategies such as crop rotation and improved seed varieties is the most effective way to improve the welfare of smallholder farmers. The average treatment effect (ATT) results show that all CCAS have a positive and significant effect on the pattern of welfare improvement among smallholder farmers, but combinations of CCAS provide the highest payoffs. As a result, the combination of crop rotation and improved seed is the most appealing CCAS package that farmers could adopt as an ex-ante strategy to improve farm household welfare. We also discovered that climate change and technology adoption are the most important factors influencing the welfare of rural farm households. Furthermore, we discover that the effectiveness of climate change adaptation strategies varies by farm households. Thus, we argued that targeted extension and advisory services, as well as other policies that support the synchronization of adaptation strategies, are critical for improving the welfare of rural farm households.

KEYWORDS

adaption strategies, climate change, multinomial endogenous switching, welfare

1 | INTRODUCTION

Climate change has the potential to have a significant impact on the welfare of farmers in various parts of the world (Troost, 2014). The unprecedented climate change affects developing countries primarily because agriculture, which is highly vulnerable to climate change, is their primary source of income (Fissha et al., 2019; Sam et al., 2020).

More than 815 million people were malnourished in 2016, and 11% of the global population experienced recent decreases in food security, with higher percentages in Africa (FAO, 2017). Climate change will cost Africa's agricultural sector 0.13% to 2% of its national output by the 21st century. The continent is unable to implement climate change mitigation strategies that would improve household welfare. Irrigation, capital, farming systems, technology,

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and high-yield varieties are thus required (IPCC, 2018). Indeed, in order to improve the poor's livelihoods and increase societal welfare, governments must prioritize reducing agricultural households' vulnerability to climate change (Bradshaw et al., 2004; Coromaldi, 2020).

Over the last two decades, Ethiopia has experienced consistent economic growth (World Bank, 2021). Agriculture employs roughly 80% of the population, accounts for 40% of GDP, and accounts for nearly 80% of export earnings (USAID, 2021). The sector, however, is impacted by a number of climate-related factors, the most significant of which are drought, flood, and unexpected rainfall (Fissha et al., 2019). Robinson et al. (2012) predict that the temperature will rise from 1.7 to 2.7°C by 2050, implying that climate change will have a significant impact on farming practices. Households are still vulnerable to risks and external shocks that cause them to fall back into or remain in poverty, especially if they are close to the poverty line. Household income varies over time due to climate variability and other shocks, and because insurance is limited, household consumption and poverty vary (Fabrizi & Mussida, 2020).

According to the literature, adaptation to climate change (crop rotation, improved seed, and irrigation) can reduce the impact of climate on household well-being (see Fissha et al., 2019; Hailu et al., 2021; Sam et al., 2020; Seaman et al., 2014; Skoufias & Vinha, 2012). Crop rotation, improved seed, and irrigation can all help to change the pattern of climate change's effect on farm income and well-being by mitigating the negative effects of climate change on farm income. Ethiopian smallholder farmers, on the contrary, have struggled to effectively implement climate change adaptation measures (Berger et al., 2017). Crop rotation and improved seed are widely used adaptation strategies in Ethiopia, as our data show that agriculture in the study areas is rain-fed, with only 2.2% of households uses irrigation.

Ethiopia has proposed climate change adaptation plans and policies in order to mitigate the effects of climate change by increasing adaptive capacity and resilience (NAP-ETH, 2019). The main components of climate change adaptation plans and policies include, among other things, mainstreaming endogenous adaptation practices and developing climate adaptation-related technologies. The need for climate change adaptation is to improve our environmental, social, and economic systems' ability to thrive and adapt to a changing climate. Understanding how farmers perceive climate change and how they adapt to it is critical for the implementation of adequate national agricultural and food security policies (Fadina & Barjolle, 2018). Farmers have adapted to changing climatic conditions, but adaptation is not as autonomous as some claim. It necessitates expertise, planning, coordination,

and foresight (Fankhauser, 2017). There are significant adaptation gaps, behavioral barriers, and market failures impeding effective adaptation and necessitating policy intervention. We have identified the most powerful national adaptation priorities in this regard, such as crop rotation (CR) and improved seed (IS) varieties, which are natural and technological, respectively.

The primary goal of this paper is to investigate the impact of climate change adaptation strategies on the welfare of Ethiopian rural farm households. We specifically investigate the differential effect of climate variables and other socioeconomic factors on farm household welfare among adopters and nonadopters of climate change adaptation mechanisms. Furthermore, we reexamined the average treatment adoption effect of combinations of climate change adaptation strategies (CCAS) on farm household welfare, and we show whether adaptation of these CCAS is effective in terms of welfare effect. In this analysis, income is a proxy variable for household welfare that is calculated by adding the multiplication of the output of a given crop and the current base year price of a specified crop.

This paper contributes to the body of literature on climate change in the following ways. To begin, in countries such as Ethiopia, where the economy is heavily reliant on an agriculture sector that is highly vulnerable to climate-related shocks, identifying robust adaptation strategies that can serve as a hedge against climate-related shocks is critical to transforming the sector and improving climate resilience. Given the scarcity of studies using panel data that are better suited to account for the dynamic nature of climate change adaptation, this study could make significant contributions to the burgeoning literature. In this regard, this is the first paper to investigate the welfare effect of climate change adaptation using three rounds of panel data from Ethiopia. Panel data analyses provide more detail, variability, and efficiency (Greene, 2003). Other advantages include panel data being suitable not only for modeling or explaining why individual units behave differently, but also for modeling why a given unit behaves differently at different times, as well as better power properties of testing procedures with dynamic analysis when compared to other methods (Verbeek, 2004). Second, whereas previous research has mostly focused on a single adaptation strategy, we look at the impact of three different adaptation strategies.

Finally, we conduct a heterogeneity analysis to identify the subset of society that the government and policymakers should focus on. Furthermore, based on farmers' adoption history and expected adoption benefit, our analysis will provide important insights for targeted policy interventions such as social protection services for poor smallholder farmers to climate change effects. In fact, this paper

contributes to a better understanding of farmers' adaptation choices by increasing knowledge of climate change adaptation, determinants of adaptation choices, and the implications of adaptation choices for societal welfare. Our findings show that combining climate change adaptation strategies can improve the welfare of smallholder farmers.

The remainder of the paper is organized as follows. The review of the literature is presented in Section 2. The conceptual and empirical framework is presented in Section 3. Section 4 delves into data and variable descriptions. Section 5 discusses the findings and results. Finally, Section 6 concludes.

2 | LITERATURE REVIEW

Adaptation measures, according to previous research, are required to mitigate climate change while increasing agricultural productivity and welfare (Deke et al., 2001; Nordhaus & Yang, 1996; Schlenker & Lobell, 2010; Skoufias & Vinha, 2012; Welch et al., 2010; Winters et al., 1996; Yates & Strzepek, 1998). Dell et al. (2014) found a negative correlation between farm income and climate change in Sub-Saharan Africa, as did Miguel et al. (2004), Barrios et al. (2010) and Hsiang (2010). However, the majority of previous studies only examined cross-sectional data, heterogeneity analysis, and a single adaptation strategy. Winters et al. (1996) investigate how general equilibrium analysis can be used to forecast how climate change will affect low-income households in developing countries. Because agriculture accounts for the majority of African countries' GDP, the results show that all African countries have significantly reduced agricultural outputs and falling household income. Adaptation strategies should focus on reducing the impact of climate change on food crop production in Africa.

Schlenker and Lobell (2010) investigate how average temperature affects yields of five major crops on a national scale. The study employs several models and independent regressions, and the results of each model and regression show that rising temperatures have a negative impact on crop production in Sub-Saharan Africa. Barrios et al. (2010) investigate the impact of rainfall patterns on the poor growth performance of Sub-Saharan Africa countries using a novel cross-country panel meteorological data set and standard ordinary least squares. Their findings show that rainfall has a significant impact on Sub-Saharan Africa's economic performance. Dercon et al. (2005) examine the impact of drought on Ethiopian household consumption using data from the Ethiopia Rural Household Survey (ERHS) across four areas, yielding a sample of 1477 households. Droughts reduce household consumption by

20%, according to the study. Deressa (2007) also examined the effects of climate change on net revenue in 50 districts using different agroecological zones. The findings demonstrated that climate has a significant impact on farmers' net revenue. Ethiopian agriculture will suffer from both rising temperatures and falling precipitation, according to projected climatic scenarios.

Fissha et al. (2019) used data from 929 rural farm households collected in 2015 to investigate the impact of crop diversification as a proxy variable of climate change adaptation strategy on farm households' well-being as measured by farm income. According to the study's endogenous switching regression model, the effects of climate variables on farm revenue differed between crop diversification adopters and nonadopters. The study also demonstrates that crop diversification adaptation contributes to farm household well-being and the development of a resilient agricultural system by having a positive and significant impact on farm revenue. Coromaldi (2020) examined the effects of weather shock on well-being using socioeconomic data from Ethiopia and discovered that rainfall variability and higher temperatures have a negative impact on output.

Tesfaye et al. (2021) investigate the welfare impact of conservation agriculture and climate-smart farming practices using a panel data endogenous switching regression model. According to the study, conservation agriculture practices can accelerate initiatives to reduce rural poverty and improve risk management for climate change. Kassie et al. (2018) also use detailed household survey data collected in 2010–11 and 2012–13, as well as panel data switching endogenous regression models, to assess the impacts of various technology adaptation decisions on farms and markets in Ethiopia. They find that decisions made with upgraded technology have a significant impact on maize yield at the farm level, with implications for welfare.

3 | CONCEPTUAL AND EMPIRICAL FRAMEWORK

We discussed the conceptual and econometric estimation strategies for estimating the effect of climate change adaptation strategies (CCAS) on farm household welfare in this section. Controlling unobserved heterogeneity and potential selection bias is required for this estimation. If the selection process is based on time-invariant unobserved heterogeneity, a panel estimator without an instrumental variable is sufficient. Selection bias, on the contrary, could occur as a result of time-varying unobserved heterogeneity (Arellano, 2003; Wooldridge, 2002). To capture time-varying unobserved heterogeneity, we

synchronize a panel estimator and endogenous switching regression (ESR). The ESR model also allows adaptation strategy options to interact with both unobserved heterogeneity and observable variables. This means that the choice of climate change adaptation strategies has an effect that is not limited to the intercept of the outcome equations but can also have a slope effect. By estimating separate regressions, ESR allows for interaction and generates a counterfactual for both adopters and nonadopters (Kassie et al., 2018).

We estimate the unbalanced panel data using the Mundlak (1978) approach, as used by Kassie et al. (2018), Khonje et al. (2018) and Tesfaye et al. (2021). We use time-varying covariates in the outcome equation and adoption equation to apply the Mundlak methods, which can estimate both random effects and fixed effects. To control time-consistent unobserved heterogeneity, we include a vector of time-averaged variables, which can avoid the problem of incidental parameters in nonlinear models like the multinomial logistic regression model. Our model is estimated using a multinomial endogenous switching regression model not only to solve the problems mentioned above but also to capture the nonseparable farmer's decision to adopt different strategies.

The estimation of the multinomial endogenous switching regression model is done in two steps. To account for unobserved heterogeneity, the first step is to estimate farmers' preferences for alternative climate change adaptation strategies¹ (Table 1). The inverse Mills ratios (IMRs) are then calculated from the estimated probabilities in the multinomial logit selection model. The second step is to evaluate the impacts of each combination of climate change adaptation strategies using ordinary least squares (OLS) with IMRs as additional covariates to avoid selection bias caused by time-varying unobserved heterogeneity.

Adapting a combination of strategies to a changing climate can be modeled using the latent variable concept and the random utility theory, which states that farmers will choose between adoption and nonadoption based on the utility they will receive. Farmers adopt climate

change strategies if they believe the utility of doing so will be greater than the utility of not doing so (Abdulai & Huffman, 2014). Let us consider the latent variable (U_{ijt}^*) below, which describes the i^{th} farmer's behavior in adopting climate change adaptation strategies (CCAS) j ($j = 1, 2, 3, 4$) at time t over any alternative CCAS combination, m :

$$U_{ijt}^* = \beta_j X_{ijt} + \theta_j X_{ij} + \varepsilon_{ijt} \text{ with}$$

$$U = \begin{cases} 1 & \text{if } U_{ijt}^* > U_{mit}^* \quad m \neq 1 \text{ max} \\ \cdot & \\ \cdot & \\ J & \text{if } U_{ijt}^* > U_{mit}^* \quad m \neq j \text{ max} \end{cases} \quad \text{for all } m \neq j \quad (1)$$

where X_{ijt} is a vector of observed exogenous covariates, β and θ are vectors of parameters to be estimated, and ε_{ijt} is the random error term.

Estimation of the multinomial logit model (MNL) could be inconsistent due to correlation of unobserved factors with explanatory variables. To address this, we follow Mundlak (1978) approach where the means (X_{ijt}) of all time-varying covariates are included as additional covariates in the MNL. Unlike the observable adoption decision, the utility derived from adoption of CCAS is unobservable. Therefore, Equation (1) entails that the i^{th} farmer will adopt a combination of CCAS j to maximize expected benefits if the adaptation provides greater utility than an alternative combination m , $m \neq j$. Then, the probability of adopting CCAS j for farmer i can be expressed as:

$$\text{pr}_{ijt} = \text{pr}(j / X_{it}, h_i) = \frac{\exp(\mu_j + X_{it}\alpha_j + h_i)}{\sum_{m \neq j} \exp(\mu_m + X_{it}\alpha_m + h_m)}, \quad j = 1, 2, 3, 4 \quad (2)$$

Therefore, Equation (2) can be estimated using MNL in the first stage.

In the second stage, we estimate the multinomial endogenous switching regression model (MESRM) to link the outcome variable (welfare) and a vector of explanatory

TABLE 1 Adoption combinations of climate change adaptation strategies.

Adaptation choice	Combinations	Frequency (%)			
		2011/12 ($n = 479$)	2013/14 ($n = 567$)	2015/16 ($n = 540$)	Full sample ($N = 1586$)
1	IS ₀ CR ₀	51.75	0.88	47.37	7.19
2	IS ₀ CR ₁	45.12	1.74	53.14	54.22
3	IS ₁ CR ₀	5.13	87.18	7.69	4.92
4	IS ₁ CR ₁	5.24	90.45	4.3	33.67

Abbreviations: IS₀CR₀, nonadopters; IS₀CR₁, adopted crop rotation only; IS₁CR₀, adopted improved seed varieties only; IS₁CR₁, adopted improved seed and crop rotation.

variables (Z) for each climate change adaptation strategy options (see Table 1). Following Tesfaye et al. (2021) and Kassie et al. (2018), the outcome equation under MESRM can be specified as:

$$\left\{ \begin{array}{ll} \text{Regime 1: } y_{it} = Z_{it}\alpha_1 + \gamma_{it}\pi_1 + (\gamma_{it}T)\omega_1 + h_{it} + v_{it} & \text{if } j=1 \\ \vdots & \vdots \\ \text{Regime } J: y_{ijt} = Z_{ijt}\alpha_j + \gamma_{ijt}\pi_j + (\gamma_{ijt}T)\omega_j + h_{ijt} + v_{ijt} & \text{if } j=2, 3, 4 \end{array} \right. \quad (3)$$

where $j = 1$ denotes that neither of the CCAS nor their combinations were adopted and $j = 2, 3, 4$ represents the adoption of either CCAS or their combinations; y_{it} and y_{ijt} are real farm household income of the i^{th} household on a plot at time t without and with adoption of CCAS set j . Z_{it} is a set of observable household, plot- and crop-level characteristics, including a time period dummy (T), that influence income at time t ; α and ω are parameters to be estimated; h_i is time-invariant unobservable household heterogeneity; γ is inverse Mills ratios derived from Equation (1) to capture time-varying individual effects; π is the covariance between the error terms of adoption and outcome equations. As in the choice model, the time-invariant unobserved variable (h) is parameterized by the mean values of time-varying explanatory variables ($\bar{z}_i$). The interaction of γ and time period dummy (T) is based on Wooldridge (2002) for estimation of unbalanced panel data models.

Following previous studies (e.g., Khonje et al., 2018; Teklewold & Mekonnen, 2017; Tesfaye et al., 2021), we select two sets of selection instruments—extension service and education-measured by year of schooling. The choice of these instruments for CCAS is based on an in-

(and individually) affect CCAS adoption decisions (see Table S2 in the Appendix S1).

Following the estimation of Equation (3), we assess the effect of the CCAS choice on the welfare outcomes (the treatment effect on the treated) in order to perform counterfactual and treatment Effects analysis. We estimate the expected actual (observed) and counterfactual outcomes for a household using CCAS set j with selection bias and endogeneity corrections. The following are the actual expected outcomes:

$$E(Y_{it,j} / j = J) = X_{it,j}\alpha_J + \gamma_{it,j}\pi_J + (\gamma_{it,j}T)\omega_J + \bar{X}_{it,j}\varphi_J, \dots j = 1, 2, \dots J \quad (4)$$

where $\bar{X}_{it,j}$ denotes the mean of the time-varying explanatory variables introduced to control for the effect of unobserved factors. Similarly, the counterfactual expected value of the outcome for farm households with CCAS set j that contains one or more adaptation components is given as follows:

$$E(Y_{it,0} / j = J) = X_{it,0}\alpha_J + \gamma_{it,0}\pi_0 + (\gamma_{it,0}T)\omega_0 + \bar{X}_{it,0}\varphi_0, \dots j = 1, 2, \dots J \quad (5)$$

The parameters $\alpha_0, \pi_0, \omega_0$ and φ_0 are the coefficients obtained from estimating the outcomes without a CCAS set ($j = 0$) and the other variables are as they are defined above. Equation (5) represents the outcome of a CCAS set j ($j = 1, \dots, J$) that adopters would have obtained if the returns (coefficients) on their characteristics had been the same as the returns (coefficients) on nonadopters' characteristics (Kassie et al., 2018; Teklewold et al., 2013). The difference between Equations (4) and (5) is used to calculate the average treatment effect on the treated (ATT), which is a measure of the average effect of CCAS on outcomes (Kassie et al., 2018; Khonje et al., 2018).

$$ATT = E(Y_{it,j} / j = J) - E(Y_{it,0} / j = J) = (\alpha_j - \alpha_0)X_{it,j} + (\pi_j - \pi_0)\gamma_{it,j} + (\omega_j - \omega_0)\gamma_{it,j}T + (\varphi_j - \varphi_0)\bar{X}_{it,j} \dots \dots \dots \quad (6)$$

sight that extension is the source of information to use the adaptation practices and farmers with better education are assumed to understand the benefits of adopting such climate adaptation strategies (Khonje et al., 2018; Tesfaye et al., 2021). It is very crucial for the X variables in MNLM to involve selection instruments in addition to automatically generated by nonlinearity of the selection model of adoption for Equation (3) to be identified. To satisfy the exclusion restriction of instrumental variables, we run a simple falsification test like previous studies (Kassie et al., 2018; Khonje et al., 2018; Tesfaye et al., 2021). We did the joint significance test that requires estimating the outcome equation alternatives which involves the instrumental variables for the validity of the instruments. The results from the first stage MLRM regression assert that the selection instruments are relevant because they jointly

The first term of Equation (6) $(\alpha_j - \alpha_0)X_{it,j}$ indicates the change in the outcomes due to the differences in the returns to the observed characteristics. The second and third terms $(\pi_j - \pi_0)\gamma_{it,j}$ and $(\omega_j - \omega_0)\gamma_{it,j}T$ indicate the change in the outcomes due to the differences in the returns that can be attributed to time-variant unobserved characteristics. The last term $(\varphi_j - \varphi_0)\bar{X}_{it,j}$ attributes to the outcome changes because of the differences in time-invariant unobservables.

4 | DATA AND VARIABLE DESCRIPTION

The Ethiopian Socioeconomic Survey (ESS), which focuses on agriculture and household well-being, was used in this study. The ESS was carried out in collaboration with

the World Bank's Living Standards Measurement Study Integrated Surveys of Agriculture program (LSMISA) and Ethiopia's Central Statistical Agency (CSA). The ESS collects comprehensive data on agricultural practices, household characteristics, household income, plot characteristics, credit, adaptation practices, climatic conditions and environmental effects, household consumption, and food security. From 2011/12 to 2015/16, household interviews were conducted in three rounds, with data collected at multiple levels. The ESS began with 3776 rural and small-town households in 2011/12. Of these, 3699 were successfully re-interviewed in the second and third waves. It implies a 2% panel attrition rate or a 98% successful follow-up rate. The ESS employed a stratified two-stage sampling strategy. Ethiopia's regions served as strata.

The enumeration areas (EAs) were chosen proportionally from each stratum based on regional population size. In this study, we used an unbalanced panel of 1586 households after thorough data cleaning and excluding observations with missing values. The joint adoption of CCAS led to four (2^2) combinations of practices from which farmers can choose (Table 1). Of the 1586 households, 7.19% were nonadopters of the CCAS. As shown in Table 1, 54.22% practiced only crop rotation (IS_0CR_1) and 4.92% only improved seed (IS_1CR_0). 33.67% of the households adopted both improved seed and crop rotation (IS_1CR_1).

The panel data were supplemented with data from the National Aeronautics and Space Administration (NASA) on temperature and rainfall. NASA's POWER-Release-8 dataset contains metrology and solar-related parameters including precipitation, rainfall, temperature, wind speed, and other geospatial data found with a spatial resolution of $0.5 \times 0.5^\circ$ for the entire globe. Assuming households situated in the same enumeration area are exposed to similar weather outcomes, we use average enumeration area coordinates (i.e., the centroid of each enumeration area) from geo-referenced ESS survey data to extract monthly average daily precipitation (i.e., the sum of daily average precipitation) and monthly average surface temperature. From these, the measures of climate variability including the coefficient of variation of precipitation and temperature are computed for each geo-referenced household.

The coefficient of variation in precipitation (measured as the standard deviation divided by the long-term mean of respective periods) computed by taking the total rainfall level during the agricultural session over 5 years before each survey round. For instance, the coefficient of variation of rainfall for the 2011/12 round is generated by taking the total rainfall level over the previous 5 years (from 2005/6 to 2011/12). Similarly, the coefficient of variation of temperature generated using the average temperature over the previous 5 years of each survey round. Rainfall and temperature highly fluctuated over time which

shows severe climate variability (see Figures S1 and S2 in Appendix S1 respectively).²

Descriptive statistics of key variables used in the analysis presented in Table 2 and Table S1 in Appendix S1. The results in Table 2 show how that the average real farm income is \$136.13 in 2015/16 is lower than \$147.08; this could be associated with drought and El Niño strikes experienced in the 2014/15 growing season.

According to Tables 2 and Table S1 of the Appendix S1, the average real farm income value is \$151, and the average total owned land is 0.4 hectares. The average rainfall and temperature vary greatly over time. Except for the year 2011/12, adopters have more physical (plot) and human capital (i.e., education) than nonadopters. Adopters also use more fertilizer than nonadopters, and their use grows over time (Table 2). Small farm households, as expected, rely on member labor rather than sharing or hiring labor. Furthermore, they plant more than one crop on their farm. We also notice that the majority of household heads are males throughout all years, and the majority of them are in their forties (around 48). The average number of school years for the three survey years (2011/12, 2013/14 and 2015/16) is 4.84. The average household size rose from 5.68 in 2011/12 to 5.84 in 2013/14 before falling to 5.79 in 2015/16 (Table 2).

With the help of institutions such as credit services and the productive safety net program (PSNP), we discovered that the proportion of farm households accessing these services increased significantly from time to time during the survey year (see Table 2). However, extension services are inconsistent across the survey year period. In general, adopters (IS_0CR_1 , IS_1CR_0 , and IS_1CR_1) have greater access to institutional support services than nonadopters (IS_0CR_1 ; see Table S2 of the Appendix S1). The results also show that adopters have more access to certificates for their land than nonadopters (Table S2). Such certification is critical for the adoption of climate change adaptation strategies because it gives farm households confidence that they can use their plot without any restriction.

5 | RESULTS AND DISCUSSIONS

5.1 | Adoption determinants of CCAS

To capture the coefficients and marginal effects, we estimated Equation (2) using a multinomial logit regression model. The average marginal effects are shown in Table 3. The results show that the marginal effects differ significantly across climate change adaptation options.

Temperature and rainfall are two climate variables that influence household adoption decisions. Average rainfall has a negative impact on the probability of using crop

TABLE 2 Descriptive statistics by survey year.

Variables	2011/12		2013/14		2015/16		Full sample	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Real farm household income in dollars	147.08	255.42	169.63	286.43	136.47	204.54	151.53	251.79
Improved seed (yes = 1)	0.07	0.25	0.97	0.17	0.05	0.23	0.39	0.49
Crop rotation (yes = 1)	0.87	0.34	0.88	0.33	0.89	0.31	0.88	0.33
Average rainfall (mm)	1179.41	421.61	1158.80	411.80	1174.90	430.59	1170.51	421.06
Average temperature (°C)	20.13	2.09	20.17	2.42	20.11	2.42	20.14	2.33
CV_ann_tem_5 (coefficient of variation in temperature for 5 years)	0.02	0.00	0.02	0.01	0.02	0.00	0.02	0.00
CV_ann_rain_5 (coefficient of variation in rainfall for 5 years)	0.22	0.07	0.26	0.09	0.29	0.08	0.26	0.09
Total fertilizer (quintal)	6.35	19.34	9.79	27.02	8.28	27.33	8.24	25.09
Household labor (numbers)	12.17	15.28	12.51	15.86	11.24	12.71	11.97	14.68
Hired labor (numbers)	4.46	82.29	2.27	16.96	3.96	62.89	3.50	59.08
Shared labor (numbers)	1.71	4.82	1.68	5.41	1.62	8.54	1.67	6.50
Plot size (hectare)	0.18	0.48	0.20	0.40	0.19	0.29	0.19	0.40
Number of crops (numbers)	1.03	0.18	1.13	0.45	1.19	0.53	1.12	0.43
Household size (numbers)	5.68	2.10	5.84	2.03	5.79	2.09	5.77	2.07
Head sex (male = 1)	0.87	0.33	0.87	0.34	0.87	0.33	0.87	0.33
Head age (numbers)	46.89	14.68	48.29	14.43	50.82	14.22	48.73	14.51
Plot slope (yes = 1)	0.09	0.28	0.11	0.31	0.11	0.31	0.10	0.30
Soil quality (yes = 1)	0.00	0.00	0.31	0.46	0.31	0.46	0.22	0.41
Pesticide use (yes = 1)	0.02	0.14	0.02	0.16	0.04	0.20	0.03	0.17
Herbicide (yes = 1)	0.07	0.26	0.12	0.32	0.14	0.35	0.11	0.31
Credit service (yes = 1)	0.29	0.45	0.27	0.44	0.23	0.42	0.26	0.44
PSNP participation (yes = 1)	0.04	0.20	0.04	0.19	0.05	0.22	0.04	0.20
Extension service (yes = 1)	0.38	0.49	0.53	0.50	0.58	0.49	0.50	0.50
Land certificate (yes = 1)	0.54	0.50	0.60	0.49	0.68	0.47	0.61	0.49
Years of schooling (Grade)	1.88	5.38	2.00	5.27	1.85	3.76	1.91	4.84

Dependent variable	Multinomial logit model (MNL) regression ME		
	IS ₀ CR ₁	IS ₁ CR ₀	IS ₁ CR ₁
Average rainfall	−0.00** (0.00)	−0.00*** (0.00)	0.00*** (0.00)
Rainfall_square	0.00*** (0.00)	0.00*** (0.00)	−0.00*** (0.00)
Average temperature	−0.01 (0.01)	0.00 (0.00)	0.00 (0.01)
CV_ann_tem_5	30.28*** (3.50)	1.53*** (0.41)	−39.65*** (3.53)
CV_ann_rain_5	0.02 (0.25)	−0.00 (0.01)	0.28 (0.25)
Total fertilizer	0.00 (0.00)	0.00 (0.00)	−0.00 (0.00)
Household labor	0.00 (0.00)	−0.00 (0.00)	0.00 (0.00)
Hired labor	−0.00 (0.00)	−0.00 (0.00)	0.00 (0.00)
Shared labor	−0.00 (0.00)	−0.00 (0.00)	0.00 (0.00)
Plot size	0.03 (0.07)	−0.00 (0.00)	−0.03 (0.07)
Number of crops	−0.03 (0.04)	0.00** (0.00)	0.00 (0.04)
Household size	−0.00 (0.02)	0.00 (0.00)	0.00 (0.02)
Head sex	0.03 (0.04)	−0.00 (0.00)	−0.02 (0.04)
Head age	0.00 (0.01)	−0.00 (0.00)	−0.00 (0.01)
Plot slope	−0.02 (0.04)	−0.00 (0.00)	0.03 (0.05)
Soil quality	−0.18*** (0.03)	0.00 (0.00)	0.20*** (0.03)
Pesticide use	0.06 (0.17)	−0.00 (0.01)	−0.08 (0.16)
Herbicide use	0.00 (0.10)	−0.00 (0.00)	−0.01 (0.09)
PSNP participation	0.09 (0.07)	−0.00 (0.00)	−0.07 (0.07)
Credit service	0.02 (0.03)	−0.00 (0.00)	0.01 (0.03)
Land certificate	0.05* (0.03)	−0.00 (0.00)	−0.04 (0.03)
Extension service	−0.08*** (0.03)	−0.00* (0.00)	0.10*** (0.03)
Years of schooling	−0.00 (0.00)	0.00** (0.00)	0.00 (0.00)
Observations	1586	1586	1586

Note: Robust standard errors in parenthesis. IS₀CR₀ is the reference category.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

rotation alone (IS₀CR₁) and improved seed alone (IS₁CR₀), but a positive impact when used together (IS₁CR₁). Rainfall, on the contrary, has an inverse relationship after a certain point, as demonstrated by the sign of the square of rainfall. When the temperature is extreme, it increases the likelihood of adopting crop rotation (IS₀CR₁) and improved seed varieties (IS₁CR₀) to cope with climate change. When farmers implement the CCAS together, the negative effect of higher temperatures is amplified. Temperature variability is also a negative and significant predictor of both improved seed and crop rotation adaptation (IS₁CR₁) but has a positive impact when these strategies are used separately.

Our findings are consistent with Fissha et al. (2019), who discovered that higher temperatures reduce agricultural system resilience and the likelihood of adopting climate change adaptation strategies. They also claimed that crop rotation, as an adaptation strategy, helps to harvest the product at a different time and with weather or environmental stress-response characteristics. Crop

TABLE 3 Marginal effects (ME) of adoption of climate change adaptation strategies.

rotation thus aids in addressing rainfall variability, high temperatures, drought, and price volatility, all of which have an impact on farm household productivity. Crop rotation and improved seed can also be used to manage pests, weeds, insects, and crop diseases (Cavigelli et al., 2013; Prasifka et al., 2006). Crop rotation, irrigation, and improved seed variety improve household welfare by increasing the ability to cope with climate change, according to Asfaw (2010), Bola et al. (2012), Hailu et al. (2021), Kuntashula et al. (2014), Tibesigwa et al. (2015), and Fissha et al. (2019).

In terms of plot-level characteristics, we find that the use of crop rotation and improved seed is positively related to fertile soils. However, the likelihood of crop rotation adoption (IS₀CR₁) is negatively related to soil quality. The findings also show that using extension services increases the likelihood of adopting crop rotation and improved seed varieties. Crop numbers have a positive and significant effect on the likelihood of farm household adaptation selection of crop rotation. Crop rotation adoption

is more likely when land certificates are available (see Table 3 of column 1). Farmers with a higher level of education can understand the advantages of using improved seed varieties. Teklewold et al. (2013) also discovered that education was also necessary for farmers in Ethiopia to adopt improved varieties.

5.2 | Impacts of adopting CCAS on farm household welfare

Table 4 depicts the impact of CCAS adoption on welfare under actual and counterfactual conditions. The findings show that adopters earned more money than nonadopters from the three CCAS options ($j = 2, 3, 4$). This implies that the use of CCAS is linked to an increase in income. Overall, the results show that combining crop rotation and improved seed (IS_1CR_1) has the highest income advantage of \$149.88. Farmers using only crop rotation (IS_0CR_1) experience the lowest income compared with those using only improved seed (IS_1CR_0 ; Table 4). Increased farm income as a result of CCAS adoption translates into increased household welfare. This is because crop income accounts for the majority of Ethiopian household income (Fissha et al., 2019). The income gains are clearly demonstrated using predicted income distribution kernel densities (Figure 1). IS_1CR_0 , IS_0CR_1 , and IS_1CR_1 have the highest kernel density of income growth than nonadopters. This is consistent with the findings of Teklewold et al. (2013) and Fissha et al. (2019) in Ethiopia, and Khonje et al. (2018) in Zambia.

We also compute the average treatment effects for only adopters. The adoption heterogeneity effect results presented in Table S4 of the Appendix S1 show that crop rotation and improved seed (IS_1CR_1) yielded the greatest gains, followed by crop rotation (IS_0CR_1). Also, we have seen results for male and female-headed households, and the results show that male-headed households benefit more from CCAS adoption. This is consistent with the findings of Khonje et al. (2018).

The rainfall variables used to instrument CA adoption are the amount of rainfall during the previous year and standard deviation of rainfall (proxy for historical climatic conditions). Both historical rainfall conditions and extension services are argued to be important drivers of CA adoption but do not directly influence the outcomes. We further observe the importance of adoption of climate change adoption strategies at different income quintiles. The results show that adoption of improved seed gives a significant relief for smallholder farmers to cope with a changing climate specifically at 0.25 and 0.5 income quintiles (see Table S5 of the Appendix S1). Likewise, at top income quintiles (0.75), adoptions of crop rotation and combined use of CCAS give a significant higher payoff for adopters.

Adopters earn more real income than nonadopters in all CCAS, according to the findings. Crop rotation and improved seed varieties both increase real household income. These findings, however, are only indicative of the effects of implementing CCAS and may be misleading due to selection bias from both observed and unobserved factors (Kassie et al., 2018; Khonje et al., 2018). Nonetheless, we find that the use of CCAS has largely had a positive impact on welfare. The adoption process is hampered by various constraints such as credit availability, land certificate, extension, rainfall and temperature shocks, and fertilizer application. This necessitates the adoption of specific policies (e.g., land tenure, fertilizer subsidy, and specific agricultural credit access policies) that can aggressively address some of Ethiopia's agricultural transformation challenges.

6 | CONCLUSIONS

This paper examined the relationship between climate change adaptation strategies and farm household welfare using a combined NASA weather geo-referenced data set and three-wave Ethiopian socioeconomic survey (ESS) panel data from 2011/12 to 2015/16. Following Mundlak (1978), we used a multinomial endogenous switching regression model (MESRM) and synchronize

TABLE 4 MESR-based average treatment effects of adoption of CCAS on household welfare.

Outcome variable	CCAS choice	Adoption status		Average treatment effects (ATE) 3 = (1)–(2)
		Adopting ($j = 2,3,4$)	Nonadopting ($j = 1$)	
		(1)	(2)	
Real household farm income	IS_0CR_1	85.19 (11.25)	59.87 (4.89)	25.32***
	IS_1CR_0	95.06 (11.41)	59.54 (4.85)	35.52***
	IS_1CR_1	149.88 (22.03)	63.89 (2.24)	85.98***

Note: j represents adoption combination of climate change adaptation strategies defined in Table 1. Standard errors in parenthesis.

*** $p < 0.01$.

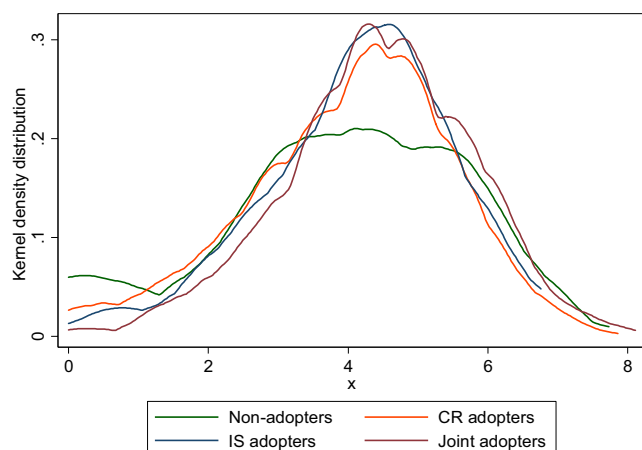


FIGURE 1 Kernel density distribution of farm income by adoption status.

the panel nature of the data to solve the problems of selection bias, cross-section estimation flaws, and unobserved heterogeneity. The average treatment effect (ATT) results show that all CCAS have a positive and significant effect on the pattern of welfare improvement among smallholder farmers, but combinations of CCAS provide the highest payoffs. As a result, the combination of crop rotation and improved seed is the most appealing CCAS package that farmers could adopt as an ex-ante strategy to improve farm household welfare. We also discovered that climate change and technology adoption are the most important factors influencing the welfare of rural farm households.

In Ethiopia, our findings have significant policy implications. According to the findings, promoting CCAS for wider adoption could result in tangible benefits for smallholder farmers in terms of increased crop productivity and household income. Overall, the findings suggest that efforts to increase household incomes should focus on encouraging the use of CCAS through the provision of improved support services such as extension and advisory services. When compared to individual adoption, joint adoption of improved seed (IS) and crop rotation (CR) would have resulted in the highest payoff. As a result, policymakers should place a greater emphasis on the joint adoption of CCAS, and climate finance programs should shift their focus to incentives for smallholder farmers to invest in CCAS that improve welfare and increase agricultural system resilience.

The findings are based on estimation techniques for multinomial endogenous switching with improved seeds and crop rotation as a climate change adaptation strategy. As a result, future research should try to include more new adaptation strategies, and analyses of CCAS' welfare impacts using more advanced techniques.

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Not applicable.

CONSENT FOR PUBLICATION

The authors assert that the manuscript has not been published and is considered for publication elsewhere.

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ENDNOTES

¹ The adoption of two climate change adaptation practices (improved seed varieties and crop rotation) involves four package choice sets (including an “empty” set where none of the strategies is adopted either singly or in combination). That means four adoption equations were estimated using the MNLM.

² The coefficient of variation in rainfall and temperature were measured for the 5 years preceding each survey years; meaning that from 2005/06 to 2011/12 for 2011/12, from 2007/08 to 2013/14 for 2013/14, and from 2009/10 to 2015/16 for 2015/16.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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