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Climate-Smart Agriculture, Non-Farm Employment and Welfare: Exploring Impacts and Options for Scaling Up

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Abstract: Climate-smart agriculture (CSA) has been receiving increasing attention in recent policy dialogues for its potential to improve agricultural transformation, risk management, and welfare. This study seeks to provide evidence on the welfare impacts of CSA adoption and its complementarity with non-farm employment using household-level data from Ethiopia combined with novel historical weather data. The study uses a multinomial endogenous switching regression model to deal with selection bias and farmer heterogeneity. The results show that households adopting CSA enjoy higher welfare benefits than non-adopter households. Households experience a higher welfare impact (lower monetary and multidimensional poverty rate) when CSA and non-farm employment are adopted simultaneously. However, there is less evidence regarding the complementarity between CSA and non-farm employment when considering per capita consumption expenditure. The study findings will have important policy implications for climate change adaptation, resilience, and poverty reduction in low-income countries.

Keywords: climate-smart agriculture; non-farm employment; welfare; heterogeneous effects; Ethiopia

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1. Introduction

Despite significant gains in poverty reduction in Sub-Saharan Africa (SSA) due to economic growth in the past two decades, rural poverty remains a concern in the region [1–3]. Agricultural households comprise a significant proportion of the population trapped in poverty because rural areas are a large harbour of poverty, mainly due to low agricultural productivity. The agriculture sector in the region continues to underperform because farmers rely on unsustainable farming practices that lead to land degradation and poor soil fertility [4–8]. Climate change emerges as a major threat to the agriculture sector and might worsen food insecurity and malnutrition in SSA [9–12]. Climate change is expected to affect smallholder farmers disproportionately in SSA; for instance, a moderate temperature increase will negatively impact cereal productions such as rice, maize, and wheat, which are mainly produced by smallholder farmers [13,14]. Given that many of the countries that will be adversely affected by climate change are in SSA and have a larger share of the poor population, there is an urgent public policy demand for identifying sustainable agricultural practices that can improve welfare and help poor farm households withstand the deleterious effects of climate change.

Due to increases in temperature and changes in rainfall patterns, and lack of structural transformation, the region is at a crossroads and facing a two-fold challenge: (i) to raise agricultural productivity to feed a surging population that is projected to reach 2 billion by 2050, to meet their changing dietary preferences, and alleviating rural poverty [15,16]; and (ii) to address the negative consequences of current and projected climate change and strengthen resilience. Given that rain-fed agriculture contributes a considerable share to Africa's GDP, addressing these challenges is a priority in the current agricultural development policy in the region; it requires a new paradigm to transform African agriculture.

The farming systems in SSA are capital deficient, prone to weather extremes, and have poor-quality soils [5,13,17]. Therefore, there is a need to develop and promote technologies and practices that improve resilience and increase agricultural productivity, thereby supporting agricultural transformation [18]. Sustainable intensification is a unique way forward for African agricultural transformation [3,19–22].

"Climate-smart" agriculture is one of the options for sustainable agricultural production that supports production and enhances adaptive capacity [15,23–25]. Recent agricultural policy has focused on these practices to address economic and environmental concerns [11,26]. CSA is an essential component of policy options designed to sustainably increase agricultural productivity, build resilience to climate risks, and mitigate climate change in SSA. It is an example of bundled programs that can have a sustainable impact on poverty because it could be a pathway to resilient escapes from poverty. CSA is also a combination of agronomic innovations that could complement other risk management tools, such as insurance and drought or stress-tolerant seeds, which are often not accessible to the rural poor. However, despite their economic and financial benefits, the uptake of CSA practices among agricultural households remains low. Explanations for this low uptake remain inadequate and unclear, particularly regarding their welfare effect and its complementarity to income risk management options such as non-farm employment.

Studies suggest that high upfront investments, yield uncertainties, and financial constraints are among the major factors that deter farmers' adoption of CSA in developing countries [27]. Another strand of the literature comprises studies that establish the link between CSA and welfare [27–33]. This study seeks to contribute to this body of literature by analyzing the impacts of CSA on monetary and non-monetary welfare outcome measures, including consumption expenditure, poverty headcount, and multidimensional poverty. Moreover, there is a dearth of evidence on the complementarity between climate risk management strategies, such as CSA, and other non-farm risk management options, such as non-farm employment and migration.

Establishing the link between CSA, non-farm employment, and welfare is important. This is because, without identifying the substitutability or complementarity of farmers' livelihood options, such as CSA and other income risk management strategies, such as non-farm employment, scaling up CSA practices only goes so far as to improve farmers' resilience. Establishing the above link is also crucial because rural households in developing countries engage in three complementary pathways out of poverty: (i) the farm pathway that entails growth in agricultural incomes, (ii) growth in non-farm incomes, and (iii) migration. Therefore, this study investigates if CSA would crowd out other income risk management strategies (non-farm employment). This is based on the hypothesis that if risk is a factor for livelihood choice and income growth [34–36], climate risk mitigation strategies in agriculture, such as CSA [2], could complement or substitute other income risk management options, such as non-farm employment.

Our research fills an important gap in the literature by illuminating the link between CSA, non-farm employment, and household welfare. The study evaluates the effects of CSA and non-farm employment (when adopted individually or in combination) on household welfare using nationally representative data from Ethiopia and a Multinomial Endogenous Switching Regression (MESR) model. We find that the impact of combining CSA and non-farm employment guarantees better household welfare compared to the case where a household is not practising CSA or engages in non-farm employment. However, CSA adoption alone appears to provide higher consumption expenditure than its combination with non-farm employment.

The rest of this paper is structured as follows. Section 2 briefly reviews the literature. Section 3 discusses the data and presents the descriptive statistics for the variables of interest. Section 4 presents the estimation strategy. Section 5 discusses the findings. The last section concludes the study and points out some policy implications of the results.

2. Literature Review

2.1. Climate-Smart Agriculture Adoption and Impacts

The agriculture sector in Ethiopia is characterized by low productivity. CSA is a sustainable agricultural practice to address climate change and poor soil fertility while helping to improve crop productivity in Ethiopia [37–39]. The promotion of CSA in Ethiopia began in 1998 across the country through field demonstrations and the training of extension agents and farmers [38]. Ethiopia's Climate Resilient Green Economy strategy also advocates using CSA for climate change adaptation [40]. However, little is known about how CSA affects household welfare and its relation to other non-agricultural livelihood strategies of rural households, particularly in Ethiopia and Africa.

Climate change harms economic growth [41], primarily through its effect on the agricultural sector [42], thus contributing to an increase in the prevalence of poverty. The most essential climate adaptation strategies are the use of improved crop varieties, crop diversification, small-scale irrigation, non-farm employment, temporary or permanent migration, and adjusted planting time [43]. CSA practices include minimum soil disturbance and residue retention, along with crop diversification, including crop rotation and intercropping. CSA has the potential to improve food security and provides a basis for poverty reduction through income, land resilience, disaster mitigation, and increased access to opportunities and ownership of assets [8].

Combining CSA techniques such as seed priming and micro-dosing of fertilizer performed the best in terms of overall farm productivity and income, which resulted in an increase in maize yield by 45% compared to traditional practices [44]. Furthermore, cultivating multiple stress-tolerant crops increased income by 83%, whereas improved livestock breeds reduced household income by 76% in Kenya [29]. Adopting stress-tolerant crops translates into increased asset accumulation, but improved livestock breeds do not affect asset accumulation, possibly as livestock can be seen as a form of savings [29]. Small-scale irrigation schemes (SSIS) can also increase production and enhance farmers' welfare; however, success mainly hinges on access to financial resources, adequate knowledge, and policy support [45].

Crop rotation, mixed cropping, improved varieties, improved nutrient management, supplementary feeding, and improved livestock housing have positive NPV values ranging between 62.56% and 227%, indicating the profitability of these CSA practices in Ghana [46]. Minimum tillage was the only examined technique that did not show profitability. The success of minimum soil disturbance or zero tillage (ZT) is often hindered by insufficient herbicide use, as the technique is known for possible increased weed infestation [47]. In addition, a lack of access to agricultural technology creates disproportionate gendered effects, as women are primarily responsible for weeding [45].

The adoption of CSA in Africa faces several challenges, limiting its potential to achieve sustainable agricultural development and food security [48]. First, there is a lack of understanding of the available policy tools that governments have at their disposal to promote climate-smart agriculture, accompanied by a lack of adequate data and information to evaluate policies. Second, the implementation and adoption of CSA techniques depend on farmers' access to information, credit, machinery, and inputs [45]. A well-established literature documents the determinants of CSA adoption in developing countries. Male-headed households have a significantly higher adoption rate of cereal–legume farming in Ethiopia, Malawi, South Africa, and Tanzania than female-headed households [37]. The results of [37] contradict the findings of [49], who found female-headed households have a higher investment in CSA than male-headed households in Malawi, Mozambique, and Zambia. Furthermore, age and education levels positively affect CSA adoption intensity [37]. CSA adoption is also shown to be common in mixed-crop livestock systems. Moreover, using chemicals is also associated with increased adoption of CSA, mainly due to the use of herbicides for zero-tilling methods. Access to credit and subsidies positively impact CSA adoption in Tanzania and Malawi but negatively impact adoption in Ethiopia. The authors indicate that this result is due to the low credit access in Ethiopia (5%) compared to Tanzania

(10%) and Malawi (24%). Larger household size is also associated with increased adoption due to increased labour availability. Access to extension and advisory services leads to increased adoption in Ethiopia and decreased adoption in South Africa, primarily due to the former having much higher quality services than the latter [37]. Households in areas with low rainfall and high evaporation adopt more CSA technologies than households that experience weather extremes.

2.2. Non-Farm Employment and Household Welfare

Participation of farm households in non-farm work has gained prominence recently as an income diversification strategy [50]. Rural non-farm employment is thought to improve welfare and ease poverty [51]. A body of literature establishes the link between non-farm employment and household welfare in developing countries, including Sub-Saharan Africa. Non-farm employment (wage and self-employment) has a positive effect on household welfare outcomes (per capita consumption expenditures) through their positive effect on the use of agricultural inputs [52]. Results further show that non-farm wage employment and non-farm self-employment are welfare-improving and poverty-reducing; however, households at the lower tail of the wealth distribution benefit significantly less than the wealthiest. Participation in non-farm work increases farm income and household welfare, providing evidence that employment opportunities outside the farm complement on-farm work [50]. Rural non-farm employment positively affects rural welfare [53] and lifts poor households out of poverty [51]. Overall, involvement in non-farm activities can offer a pathway out of poverty—but only if there are sufficiently productive and remunerative opportunities available and if poor households can take advantage of them [54]. This needs effective strategies to increase the incomes of poor rural households as they diversify farm production and move into rural non-farm economic activities to enhance off-farm job creation. There is also a large body of knowledge that documents the factors that influence participation in non-farm work, including household demographic characteristics (sex, age, dependency ratio), education, wealth, including farm size and credit access [50,55], agro-ecological potential, and urban access [56]. However, no evidence exists on whether prompting non-farm employment complements or substitutes other income risk management options such as CSA. Using representative survey data from Ethiopia, this study sheds light on the link between CSA, non-farm employment, and household welfare.

3. Data

3.1. Household Survey Data

This study uses data from the latest round of the Ethiopian Socioeconomic Survey (ESS) collected under the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) of the World Bank in collaboration with the Central Statistical Agency (CSA) of Ethiopia. ESS is publicly available rich, georeferenced, nationally representative (at both the urban and rural levels) household survey data. It provides a rich array of information on household characteristics, income sources, household assets, consumption expenditure, shocks, coping strategies, food security, land holdings, crop production, and livestock ownership. The survey collects data on households from 2011 to 2016 in three waves (2011/12, 2013/14, and 2015/16). However, the 2018/19 ESS is a new panel, and hence we could not exploit the panel structure of the data. ESS has an agriculture module that captures detailed information on CSA practices, post-planting, and post-harvest activities, including landholding, crop production and disposition, and livestock ownership. In addition to the household data, the survey solicited community-level information on access to public services, such as infrastructure, markets, and health services. The georeferencing of the households enables us to merge household data with geospatial climate information.

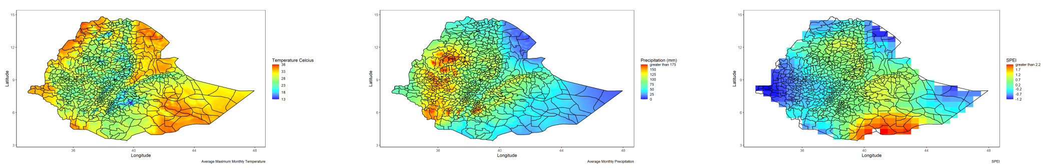
3.2. Climate Data

We merge the household data with temperature and precipitation data obtained from the Climatic Research Unit (CRU-TS-4.03), University of East Anglia [57]. We use the downscaled version that corrects for bias, which is produced by WorldClim [58]. The temperature variable measures the average near-surface maximum temperature in degrees Celsius, and the precipitation variable measures total precipitation in millimetres.

The temperature and precipitation data are gridded monthly time-series data for the period between 1960 and 2018 with a spatial resolution of 2.5 min and roughly 21 km^2. Using this data, we used the households' GPS coordinates (latitude and longitude) to create a five-kilometre buffer around each point. We then used this five-kilometre buffer to merge the precipitation and temperature data within the buffer for each household. Next, we followed a similar strategy to merge the household data with the Standardised Precipitation Index (SPI) data from University Corporation for Atmospheric Research (UCAR). However, we create a ten-kilomette buffer for the SPI due to data availability. The SPI is used to characterize meteorological drought. On short timescales, such as our context, the SPI is closely related to soil moisture, while at longer timescales, the SPI can be related to groundwater and reservoir storage.

The temperature, precipitation, and SPI are calculated as monthly averages. The monthly average for 2018/19 was taken from July (post-planting) of the survey year to June (post-harvesting). This allows capturing the climate variability span of the post-planting and post-harvesting stages of the LSMS-ISA dataset. We use these variables in the estimation to account for climate variability's short- and longer-term effects on household livelihood choices.

Figure 1 presents the temperature, precipitation, and SPI data. Existing studies suggest that the welfare effect of climate change (change in temperature and precipitation) takes time [59], and the indirect effects, such as water scarcity, displacement, uncertainty, and food security, are a substantial threat and can cause long-lasting welfare damage [60]. Therefore, we include temperature$_{t-3}$'s and precipitation$_{t-3}$'s in the regressions instead of using the same year average of the climate variables. We also check the effect of one lag temperature and precipitation, the qualitative results remain unchanged. Results are available from authors on request.



(**a**) Temperature (**b**) Precipitation (**c**) SPI

Figure 1. Temperature, precipitation, and SPI, 2018/19.

3.3. CSA and Non-Farm Employment

Farmers in rural Ethiopia adopt a wide range of CSA practices. We construct an index for CSA adoption using principal component analysis (PCA). PCA is preferred to the additive index because it produces a more effective measure by recovering the underlying latent variable [61]. To construct the CSA adoption variable, we consider cereal–legume intercropping, zero tillage, natural fertilizers, improved seeds, irrigation, soil conservation, and crop rotation variables that are collected in the ESS. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy for the CSA practices we considered is 0.53, supporting the use of PCA for the analysis. The PCA results show that the first three components had eigenvalues greater than one—dominating in terms of eigenvalues and proportion of variance. The components vector also contains positive weights for all the CSA practices, suggesting that the aggregate variation in our score results from household variation in adoption levels [62]. Thus, we classified households based on the three PCA scores, with PCA scores greater than zero as adopters of CSA and those with less than or equal to zero as non-adopters.

To explore the complementarity (substitutability) of CSA with non-farm employment, we constructed a non-farm employment variable. Non-farm employment is defined at the household level as a binary variable taking a value of 1 if the household participates in (generates income from) wage employment or self-employment (enterprises) or receives a transfer from a migrated household member, 0 otherwise.

Following the above definitions, the treatment indicator or adoption variable is defined as a polychotomous variable with four possible discrete outcomes: (i) none (a household adopted neither CSA nor non-farm employment), (ii) CSA only, (iii) non-farm employment only, and (iv) both (a household adopted CSA and non-farm employment simultaneously).

3.4. Welfare Outcomes

The welfare outcomes include consumption expenditure per adult equivalent per year, monetary poverty (based on the bottom 40% of the consumption expenditure), and a multidimensional poverty index (MPI). The consumption expenditure per adult equivalent value is obtained by aggregating the value of food and non-food spending at the median prices. The median prices are calculated at the lowest geographical unit for which there are at least 10 price observations. If there are less than 10 price observations for that item at the enumeration area (EA), the next level up is used. The geographical levels used, in ascending order, are EA, Kebele, Woreda, zone and region, and national. The aggregate consumption expenditure is adjusted for differences in the nutritional or calorie requirement of different household members by dividing it with an adult equivalence scale. Given that our analysis focuses on rural households and the incidence of poverty is higher in rural areas of Ethiopia, using the national poverty line overestimates the poverty rate. Thus, we used 40% of the average annual consumption expenditure per adult equivalent as a poverty line threshold. Monetary poverty is a binary variable taking a value of 1 if the per adult equivalent expenditure per year is less than the 40th percentile of the annual consumption expenditure per adult equivalent (i.e., Birr 9254) and 0 otherwise. The multidimensional poverty index (MPI) is constructed using three main dimensions (education, health, and living conditions) and nine sub-dimensions following the methodology developed by [63]. Education and health indicators are weighted 1/6 and 1/3 each, respectively, and the standard of living indicators are weighted 1/18 each. Under education, we considered years of schooling (At least one child aged 7–15 years is not attending school) and school attendance (No one in the household has at least 6 years of education). For the health dimension, we considered whether at least one 6–59-month-old child in the household is stunted. Finally, under living standards, we include access to electricity, access to improved water, access to an improved sanitation facility, access to safe cooking fuel (household does not use solid cooking fuel such as wood, charcoal, leaves, or manure), floor type (household does not have a quality finished flooring) and ownership of assets (household does not have a radio, TV, or phone or no transportation asset and no refrigerator). MPI is a binary variable taking a value of 1 if a household is multidimensionally poor and 0 otherwise.

Households that adopt CSA or participate in non-farm employment have higher consumption expenditures than non-adopters (Figure 2). There is a statistically significant difference in consumption expenditure between the different groups of households: none (non-adopter), CSA, non-farm employment, and both CSA and non-farm employment. Adopters (of CSA or non-farm employment in isolation or combination) have higher consumption expenditure, on average, than non-adopters. Comparing the livelihood options, households that adopt CSA and participate in non-farm employment have the highest average consumption expenditure, followed by those that participate in non-farm employment only and those that adopt CSA only. Figure 2 further shows that, on average, female-headed households (FHH) adopting one or both of the livelihood options had a higher consumption expenditure than their male counterparts (MHH).

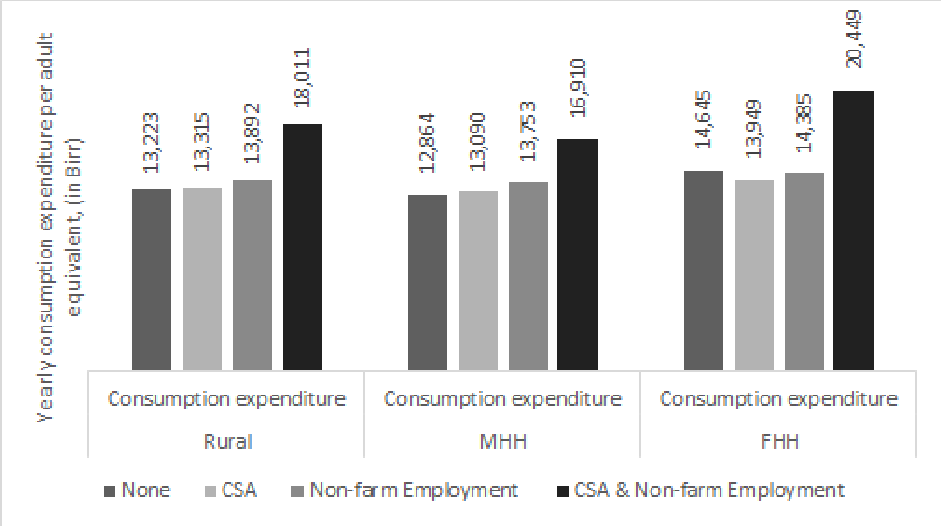


Figure 2. Consumption expenditure per adult equivalent per year (in Birr) by livelihood options and gender.

Figure 3 presents monetary and multidimensional poverty rates by livelihood options and gender of the household head. In line with our observation in Figure 2, households that adopt the two livelihood options simultaneously have lower monetary and multidimensional poverty rates. Similarly, FHHs that adopt non-farm employment and CSA jointly have the lowest monetary and multidimensional poverty rates.

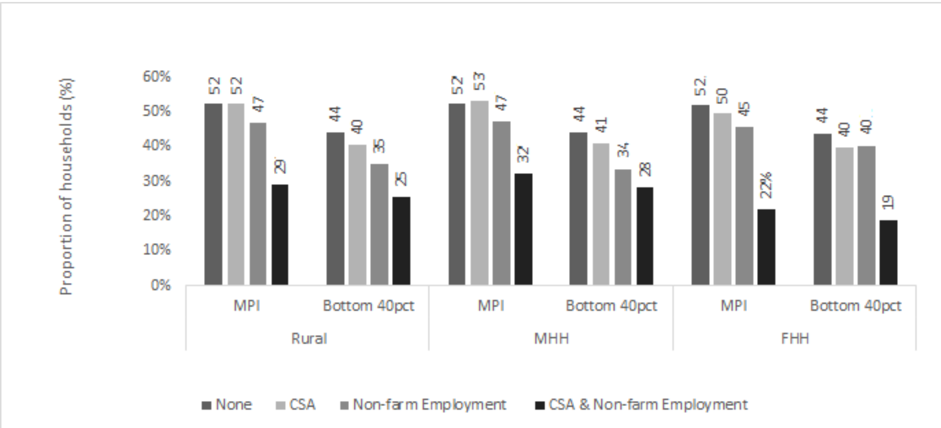


Figure 3. Poverty rates (MPI and monetary poverty) by livelihood options and gender.

3.5. Control Variables

The control variables used in the regressions include socioeconomic and demographic characteristics (gender of head, age of head, household size, and head education), wealth (livestock holding and land holding), proximity to services (distance to roads and markets), extension reach, shocks experience, and climate variables. The choice of the variables is based on a review of the existing literature, economic theory, and data availability. Table A1 in Appendix A provides the summary statistics of the main explanatory variables used in our analysis by adoption status: none, CSA only, non-farm employment only, and both.

4. Empirical Strategy

The biggest challenge in estimating the effect of non-random self-selected interventions is finding a credible estimate of the counterfactual: what would have happened to treated households, for instance, households that adopt CSA if they had not adopted CSA? If adoption is randomly assigned, the difference in the outcome between CSA non-adopters (untreated households) and CSA adopters (treated households) can be a reasonable estimate of the treatment effect. However, households that adopt that livelihood option may have characteristics that differ from the ones that do not adopt it [64]. Without information on why households self-select to adopt one or more strategies, the next best alternative is to construct a counterfactual (a comparison group), which is as close as possible tothe treated households; those who adopt CSA and non-farm employment would have had similar outcomes in the absence of the treatment [64,65]. We use a multinomial endogenous switching regression model (MESR) that allows deriving the impacts of CSA adoption and non-farm employment on household welfare while addressing selection bias.

Let there be $(P+1)$ exclusive livelihood options or climate risk management strategies whereby the possible strategies are denoted using $(Y_0, Y_1, \ldots, Y_P)$. For each household, only one state of the potential strategy is observed, and the other states are counterfactuals. The adoption of a particular strategy (CSA, non-farm employment, or both) is donated by $T\{0,1,\ldots,P\}$. There are $P+1$ potential outcomes for each household, but there is only a single state strategy that is observed (T_i). Thus, for a household $i, T_i = t$, then $Y_i = Y_i[t] = \mu_t$. In the context we are working, where households adopt one or more strategies, we emphasize the comparative efficacy of all strategies jointly and separately.

In this framework, the relative average treatment effect (ATE) of strategy t' relative to t'' is the difference in average outcomes had all households been observed under a single strategy t versus had all households been observed under the alternative strategy t'' [66,67].

Formally, ATE $(t^{t't''}_{ATE})$ is given as follows:

$$\tau^{t't''}_{ATE} = \mu_{t'} - \mu_{t''} \tag{1}$$

The average treatment on the treated (ATT) is the pairwise contrast of the effects of the strategy and t'' for households in either t' or t''. Thus ATT is given in Equation (2):

$$\tau^{t't''}_{ATT} = \mu_{t't''} - \mu_{t't'} \tag{2}$$

The relative ATT of treatment (t') among households that adopt strategy t'' is the difference between the mean outcome of those who adopt strategy t'' and those who adopt t' would have had if they had been adopted t'' instead of t' (Araar et al., 2019 [66]; Wooldridge 2010 [67]).

In this study, we aim to identify the combination of CSA and non-farm employment that is most beneficial to improving the welfare of farm households. Thus, we estimate and report both ATE and ATT. While ATE sheds light on the gain in welfare (the treatment effect) if all farm households adopt a particular strategy, ATT provides information on the relative effectiveness of one strategy versus another. Therefore, we estimate and report ATE and ATT to provide complete information, as summarized in Table 1.

Table 1. Treatment effects (ATE and ATT) of multiple treatments.

	ATE		**ATE**	**ATT**		
				CSA (csa)	**Non-Farm (nf)**	**Both (Both)**
CSA vs. non-adopters (ni)	$\mu_{csa} - \mu_{ni}$	CSA vs. Non-farm	$\mu_{csa} - \mu_{nf}$	$\mu_{csa,nf} - \mu_{csa,csa}$	$\mu_{csa,nf} - \mu_{nf,nf}$	§
Non-farm vs. Non-adopters (ni)	$\mu_{nf} - \mu_{ni}$	CSA vs. Both	$\mu_{csa} - \mu_{both}$	$\mu_{csa,both} - \mu_{csa,csa}$	§	$\mu_{both,csa} - \mu_{both,both}$
Both vs. Non-adopters (ni)	$\mu_{both} - \mu_{ni}$	Non-farm vs. Both	$\mu_{nf} - \mu_{both}$	§	$\mu_{nf,both} - \mu_{nf,nf}$	$\mu_{both,nf} - \mu_{both,both}$

§ non-sensical cases to estimate the ATT.

A farming household's choice between CSA and/or non-farm employment or the simultaneous adoption of both may be endogenous to observed and unobserved characteristics of households leading to self-selection bias. As discussed above, to address potential self-selection bias due to observed and unobserved characteristics of households, we use the multinomial endogenous switching regression approach following Dubin and McFadden (1984). Using this approach, we first model the livelihood strategy decision (CSA, a combination of CSA and non-farm employment, or neither) using a multinomial logit selection model that accounts for the interdependence between the strategies. Then, the effects of each strategy on welfare (consumption expenditure per adult equivalent and monetary and multidimensional poverty) are assessed using a linear regression model with endogenous treatment effects.

Let (T_{ji}) describe household i's choice of CSA and non-farm employment j over another alternative p; given as follows.

$$T_{ji} = \gamma_j z_i + \varepsilon_{ji} \tag{3}$$

where z_i is the vector of observable characteristics of households and their members that affect the choice of CSA and non-farm employment, such as gender of household head, age, education, household size, land size, ownership of livestock, distance to market, access to extension services, temperature, and precipitation. $\varepsilon_i j$ is the unobservable characteristic that affects the adoption decision of one or more strategies. The utility of adopting an alternative CSA practice is not observed, while the actual adoption of a given practice is observed. A household's choice of a practice j over an alternative practice m is given by:

$$T_{ji} = \begin{cases} 0 \; if \; T_{ji} > \max_{m \neq 1} T_{mi} \;\; or \; \omega_{0i} < 0 \\ \quad . \quad . \quad . \\ \quad . \quad . \quad . \\ \quad . \quad . \quad . \\ J \; if \; T_{ji} > \max_{m \neq j} T_{mi} \;\; or \; \omega_{ji} < 0 \end{cases} \tag{4}$$

where $w_{ji} = \max_{m \neq j}(T_{mi} - T_{ji}) < 0$ (Bourguignon et al., 2007 [68]). Equation (4) implies that household i chooses alternative practice j over m if and only if the welfare gain from j is greater than that welfare obtained from m for $m \neq j$.

Assuming that ε is an independent and identical distribution, the probability that household i will adopt a given CSA practice and/or non-farm employment j given its characteristics z can be given as a multinomial logit model, as in Equation (5) [69].

$$p_{ji} = pr(\omega_{ji} < 0|z) = \frac{\exp(\gamma_j z_i)}{\sum_{m=1}^{J} \exp(\gamma_m z_i)} \qquad j = 1, 2, \ldots, J \tag{5}$$

The following multinomial endogenous switching regressions are specified to evaluate the effect of each livelihood strategy on the welfare of households:

$$c_{ni} = \beta_n x_i + u_{ni} \qquad if \quad T = 0 \tag{6a}$$
$$c_{csai} = \beta_{csa} x_i + u_{csai} \qquad if \quad T = 1 \tag{6b}$$
$$c_{nfi} = \beta_{nf} x_i + u_{nfi} \qquad if \quad T = 2 \tag{6c}$$
$$c_{bothi} = \beta_{both} x_i + u_{bothi} \qquad if \quad T = 3 \tag{6d}$$

where c_{ni}, c_{csai}, c_{nfi}, and c_{bothi} are the four discrete outcomes representing non-adopters, those that adopt CSA only, non-farm employment only, and both CSA and non-farm employment, respectively. x_i is the vector of observable characteristics that affect the choice of CSA and non-farm employment, such as gender of household head, age, education, household size, land size, livestock ownership, distance to market, access to extension services, and climate variables.

Due to possible confounding factors, such as motivation to work and risk-taking behaviour, that affect the outcome variable in the above equations and the selection equation, estimating the above equations using OLS yields biased results. Hence, consistent estimates of the parameters require correction for selectivity. In addition to the selectivity bias correction obtained from the multinomial logit model (the inverse Mills ratio -IMR terms), we have considered an exclusion restriction variable that is used as the IV. The IV is the village-level CSA adoption rate calculated by excluding the household under consideration to avoid possible reverse causality in that the household's CSA adoption decision affects the CSA adoption decision at the village level. The basic argument for using the village-level CSA adoption as an IV is that agricultural technology adoption and production decisions are likely to be influenced by the decision of neighbouring households due to peer effects and learning externality [70,71]. Farmers in the same neighbourhood face similar demographic, institutional, and economic challenges and thus are likely to adopt similar production systems [70,72]. Thus, CSA adoption at the village level will affect the livelihood choice of households. The IV is expected to not be correlated with the unobserved household heterogeneity and the household consumption or poverty status [71,72].

According to [68], consistent estimates of the parameters can be obtained by introducing a correction term in the above equations as follows:

$$c_{ni} = \beta_n x_i + \sigma_n \lambda_n + \xi_{ni} \quad if \quad T = 0 \tag{7a}$$

$$c_{csai} = \beta_{csa} x_{ji} + \sigma_{csa} \lambda_{csa} + \xi_{csa} \quad if \quad T = 1 \tag{7b}$$

$$c_{nfi} = \beta_{nf} x_{ji} + \sigma_{nf} \lambda_{nf} + \xi_{nf} \quad if \quad T = 2 \tag{7c}$$

$$c_{bothi} = \beta_{both} x_{ji} + \sigma_{both} \lambda_{both} + \xi_{both} \quad if \quad T = 3 \tag{7d}$$

where σ_u is the covariance between ε and u. λ is the correction term (the mills ratio given in Equation (8) below) derived based on estimated probabilities from the first equations (Equation (5)) and the correlation (p) between ε and u.

$$\lambda_j = \sum_{m \neq j}^{J} \rho_j \left[\frac{\widehat{P_{mi}} \ln\left(\widehat{P_{mi}}\right)}{1 - \widehat{P_{mi}}} + \ln\left(\widehat{P_{ji}}\right) \right] \tag{8}$$

Following this, we can estimate the expected household welfare (consumption per adult equivalent and poverty) for untreated farming households as follows:

$$E(c_{ni} T = 0) = \beta_n x_i + \sigma_n \lambda_n \tag{9a}$$

Similarly, the expected household welfare of households that adopt the different strategies under investigation are given as follows:

$$E(c_{csai} | T = 1) = \beta_{csa} x_i + \sigma_{csa} \lambda_{csa} \tag{9b}$$

$$E(c_{nfi} | T = 2) = \beta_{nf} x_i + \sigma_{nf} \lambda_{nf} \tag{9c}$$

$$E(c_{Bothi} | T = 3) = \beta_{Both} x_i + \sigma_{Both} \lambda_{Both} \tag{9d}$$

Comparably, the expected value of consumption per adult equivalent or poverty for non-adopters had they adopt one or more strategies is given as follows:

$$E(c_{ji} | T = 0) = \beta_j x_i + \sigma_j \lambda_n \tag{10a}$$

Finally, the expected value of consumption per adult equivalent or poverty for those that adopted j had they not adopted any of the strategies is given :

$$E(c_{ni} | T = j) = \beta_n x_i + \sigma_n \lambda_j \tag{10b}$$

t' and t'' are treatments in j ATE and ATT are computed as follows:

$$ATE_j = E(c_{ji} | T = j) - E(y_{ni} | T = n) = \beta_j x_{ji} + \sigma_j \lambda_j - \beta_n x_{ni} + \sigma_n \lambda_n \tag{11a}$$

$$ATE_{t't''} = E(c_{t'} | T = t') - E(c_{t''} | T = t'') = \beta_j x_i + \sigma_j \lambda_j - \beta_n x_{ni} + \sigma_n \lambda_n \tag{11b}$$

$$ATT_j = E(c_{ji} | T = j) - E(c_{ni} | T = j) = (\beta_j x_i + \sigma_j \lambda_j) - (\beta_n x_i + \sigma_n \lambda_j) \tag{12a}$$

$$ATT_{t't''} = E(c_{t''} | T = t') - E(c_{t'} | T = t') = (\beta_{t''} x_i + \sigma_{t''} \lambda_{t'}) - (\beta_{t'} x_i + \sigma_{t'} \lambda_{t'}) \tag{12b}$$

5. Results

This section presents and discusses the MESR model results that provide estimated impacts of CSA and non-farm employment on welfare outcomes, annual consumption per adult equivalent, and monetary and multidimensional poverty.

5.1. Impacts on Consumption Expenditure

We start our analysis by estimating the welfare effects of CSA and non-farm employment on household consumption expenditure per adult equivalent. The ATE shows the difference in consumption expenditure for all households who had adopted a specific strategy and the comparison group. First, we computed ATE by comparing the consumption expenditure for households that adopt one or both strategies with non-adopters. Second, we computed ATE by comparing each strategy to another. The results show that both CSA and non-farm employment have positive welfare impacts (Table 2) The results are based on the second stage of the MESR model. Table A4 in Appendix A presents the full results. However, the highest welfare benefit is obtained when CSA is adopted in isolation, even compared to the simultaneous adoption of both CSA and non-farm employment. The ATE for all households who adopted CSA compared to non-adopters is an increase in consumption expenditure of about Birr 3089. This is in line with previous studies that document a positive welfare effect of CSA in Africa [27–33]. The corresponding effect of non-farm employment is Birr 1566. The ATE for households who adopted both CSA and non-farm employment compared to non-adopters is positive but insignificant. The results suggest that the two livelihood strategies are substitutes, and we document non-farm employment's crowding-out effect of CSA adoption. The possible explanation for the observed results could be their competition for productive labour. The potential channels through which CSA and non-farm employment affect household welfare include increased farm production, reduced costs of production, and risk mitigation [2,30,32,33].

Table 2. ATE estimates of CSA, non-farm employment, and their combination on consumption expenditure.

ATE			
CSA vs. Non-adopters	3089 ***	CSA vs. Non-farm	1522 ***
Non-farm vs. Non-adopters	1566 ***	CSA vs. Both	2916 ***
Both vs. Non-adopters	172	Non-farm vs. both	1394 ***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Comparing the impact of CSA and non-farm employment, the ATE for households that adopted non-farm employment show that consumption expenditure could have increased by 1522 Birr had they adopted CSA. Similarly, adopting CSA instead of both CSA and non-farm employment would have increased consumption expenditure by about Birr 2916. Finally, the ATE for households that adopt both CSA and non-farm employment shows that their consumption expenditure would have increased by Birr 1394 had they adopted non-farm employment alone. The declining welfare effect of changing strategies from CSA to non-farm employment highlights the difference in the effectiveness of CSA in improving welfare compared to non-farm employment. Overall, the ATE estimates suggest that the adoption of CSA improves the welfare of households more than non-farm employment and the combination of CSA with non-farm employment.

The ATT results show that moving from CSA to non-farm employment has a positive but no significant impact on consumption expenditure. However, moving from CSA to both CSA and non-farm employment led to a significant decline in consumption expenditure (by Birr 2156) compared to adopting CSA alone. This suggests that the consumption of households that adopted CSA alone could have declined had they chosen to adopt both CSA and non-farm employment simultaneously. For those that adopt only non-farm employment, the ATT of the shift from non-farm employment to CSA is an increase in consumption expenditure by about Birr 2599. Conversely, the ATT of moving from non-farm employment to both CSA and non-farm employment was a decline in annual consumption expenditure of about Birr 2720. Focusing on households that adopt both strategies, adopting non-farm employment alone and CSA increased average annual consumption expenditure, though the results are insignificant. This suggests that combining CSA and non-farm employment is not more effective in enhancing the welfare of rural households than adopting the two strategies separately (Table 3).

Table 3. ATT estimates of CSA, non-farm employment, and their combination on consumption expenditure.

	ATT		
	CSA	**Non-Farm**	**Both**
Non-farm vs. CSA	1416	2599 ***	§
Both vs. CSA	−2156 ***	§	1092
Both vs. Non-farm	§	−2720 ***	629

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. § non-sensical cases to estimate the ATT.

5.2. Impacts on Monetary Poverty

Table 4 provides the ATE estimates of the impacts of CSA, non-farm employment, and their combination on monetary poverty. The ATE results show that households that adopt CSA are less likely to be poor (have a consumption expenditure of less than 40% of the national average or be in the bottom 40%) compared to non-adopters. The results further show that non-farm employment (compared to non-adopters) will decrease the probability that a household would be poor (in the bottom 40%) by 13.7 percentage points. The results also show that households that adopt CSA and engage in non-farm employment are less likely to be poor compared to non-adopters. The plausible explanation is that poor households in rural Ethiopia tend to be larger [73]; this might relax the labour constraints of low-income families, allowing them to adopt diversified livelihood strategies jointly and thus benefit more by combining the different strategies considered in the study.

Comparing the impacts of CSA and non-farm employment on poverty, the ATE estimate of adopting CSA instead of non-farm employment is insignificant. Adopting both strategies instead of CSA or non-farm employment individually would increase poverty by 11 and 10 percentage points, respectively. The ATE estimates suggest that adopting CSA and non-farm employment jointly reduces poverty more than adopting the livelihood options separately. Overall, the results indicate that the two livelihood options are complementary because their combination has the highest poverty-reducing effect.

Table 4. ATE estimates of CSA, non-farm employment, and their combination on monetary poverty.

ATE			
CSA vs. Non-adopters	−0.129 ***	CSA vs. Non-farm	0.008
Non-farm vs. Non-adopters	−0.137 ***	CSA vs. Both	0.110 ***
Both vs. Non-adopters	−0.239 ***	Non-farm vs. Both	0.103 ***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The ATT estimates for the impacts of CSA, non-farm employment, and their combinations are presented in Table 5. Adopting CSA instead of non-farm employment would reduce poverty by 7.4 percentage points in adopting households. However, adopting CSA separately would increase poverty (by 7.2 percentage points) of those that adopted both livelihood options jointly. This suggests that poverty would decline if households jointly adopted CSA and off-farm employment. For those that engage only in off-farm employment, the ATT of the shift from non-farm employment to CSA adoption is insignificant. Moreover, the ATT of moving from non-farm employment to both CSA and non-farm employment shows a decline in poverty by 8.9 percentage points. This suggests that combining CSA and non-farm coping strategies improves household welfare more effectively than adopting the two strategies separately.

Table 5. ATT estimates of CSA, non-farm employment, and their combination on monetary poverty.

	ATT		
	CSA	**Non-Farm**	**Both**
Non-farm vs. CSA	−0.074 ***	0.001	§
Both vs. CSA	0.072 **	§	0.021
Both vs. Non-farm	§	−0.089 ***	0.047

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. § non-sensical cases to estimate the ATT.

5.3. Impacts on Multidimensional Poverty

We used the multidimensional poverty index (MPI) as an additional welfare measure to show the effect of CSA adoption and non-farm employment on non-monetary welfare indicators. The results show that CSA adoption, non-farm employment, and their combination reduce the probability of being poor (in non-monetary terms) by 8, 10, and 36 percentage points, respectively, compared to non-adopters (Table 6). The results show that the combination of CSA and non-farm employment generates the highest poverty-reducing benefits than the adoption of CSA or non-farm employment. This provides evidence of the complementarity between CSA and non-farm employment.

Table 6. ATE estimates of CSA, non-farm employment, and their combination on MPI.

	ATE		
CSA vs. non-adopters	−0.081 ***	CSA vs. Non-farm	0.021 ***
Non-farm vs. non-adopters	−0.103 ***	CSA vs. Both	0.280 ***
Both vs. non-adopters	−0.362 ***	Non-farm vs. Both	0.259 ***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The ATT estimates for the impacts of CSA, non-farm employment, and their combination are presented in Table 7. Moving from CSA to non-farm employment, poverty decreases by 15.5 percentage points. However, moving from CSA to both led to an increase in the multidimensional poverty rate by 18.2 percentage points. This suggests that multidimensional poverty would decline had they adopted both CSA and non-farm employment. For those that engage only in non-farm employment, the shift from non-farm employment to CSA adoption would increase multidimensional poverty by 2 percentage points. Moreover, moving from non-farm employment to both CSA and non-farm employment would reduce multidimensional poverty by 28.4 percentage points. This suggests that combining CSA and non-farm employment is more effective for improving household welfare (by reducing non-monetary poverty) than adopting the two strategies separately.

Table 7. ATT estimates of CSA, non-farm employment, and their combination on MPI.

	ATT		
	CSA	**Non-Farm**	**Both**
Non-farm vs. CSA	−0.155 ***	−0.020 ***	§
Both vs. CSA	0.182 ***	§	0.149 ***
Both vs. Non-farm	§	−0.284 ***	0.065

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. § non-sensical cases to estimate the ATT.

5.4. Heterogenous Effects by Consumption Quintiles

We use quantile regression to shed light on the heterogeneous effects of CSA and non-farm employment on consumption expenditure (our primary welfare measure. These estimates are not comparable with the MESR model because unobserved heterogeneity and self-selection are not addressed. The quantile regression helps to test whether CSA and non-farm employment have significantly different household welfare effects between high- and low-income households. Investigating the heterogeneous impacts can help to identify policy options that are better tailored to the needs of a socioeconomically diverse smallholder population. Furthermore, going beyond the average effect, the results are expected to be more homogeneous since farmers located at the same point of the income distribution are more likely to follow the same livelihood pathway and adopt similar strategies. Table 8 reports the estimated coefficients associated with the CSA, non-farm employment, and their combination at four points of the consumption expenditure distribution (quantiles 0.2, 0.4, 0.6, and 0.8).

Table 8. Heterogenous effects of CSA and non-farm employment on welfare: quantile regression estimates.

	q = 20	q = 40	q = 60	q = 80
CSA	867.27 *	1542.63 ***	1402.42 ***	1654.86 *
	(492.31)	(400.16)	(512.28)	(979.68)
Non-farm employment	945.76 ***	1199.55 ***	1975.29 ***	2018.21 **
	(357.17)	(460.65)	(467.93)	(817.55)
CSA and non-farm employment	2503.81 ***	2866.60 ***	4014.27 ***	4468.35 **
	(656.21)	(863.08)	(1160.73)	(2059.5)

Note: Untreated is the base outcome. The regressions include all control variables and region dummies included in the MESR model. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The results highlight that the average effects of the adoption of CSA, non-farm employment, and both increase linearly across the consumption expenditure quintiles. The adoption of CSA increases per adult equivalent consumption expenditure by Birr 867 for the poorest (q = 0.2) and by Birr 1655 for the richest (q = 0.8) households. A similar pattern is found for the impact of non-farm employment: moving from the bottom to the top of the consumption expenditure distribution, the effect of non-farm employment monotonically increases (from Birr 946 to Birr 2018). A higher welfare impact is achieved when CSA and non-farm employment are adopted simultaneously. The poorest rural households that adopt both CSA and non-farm employment have higher consumption expenditure (Birr 2504). However, the richest households earn, on average, more than the poorest (Birr 4468). Overall, the results highlight that CSA and non-farm employment (and their combination) have higher welfare effects among the richest than for the poorest rural households. A study in Malawi also found that non-farm employment positively affects household welfare outcomes (per capita consumption expenditures), where the magnitude of the impact is larger for the wealthiest households than those at the lower tail of the welfare distribution [52]. The relatively lower effect for the poorest could be due to the limited capacity of the rural poor to adopt CSA and participate in non-farm activities.

6. Conclusions and Policy Implications

Climate-smart agriculture (CSA) has received increasing attention in recent policy dialogues for its potential for agricultural transformation, risk management, and welfare improvement. This study provides evidence on the welfare impacts of CSA adoption and its complementarity with non-farm employment. For this purpose, we estimate the impacts of CSA when adopted in isolation and in combination with non-farm employment on monetary (yearly household consumption expenditure and monetary poverty) and non-monetary (multidimensional poverty index) welfare outcomes using household-level data from Ethiopia combined with novel historical weather data. The study uses a multinomial endogenous switching regression model to deal with selection bias and farmer heterogeneity.

Two results are worth stressing. First, the impact of combining CSA and non-farm employment guarantees better income risk management compared to the case where a household is not practising CSA or engages in non-farm employment. Our result shows that households that adopt both CSA and non-farm employment simultaneously have lower poverty rates than non-adopters. Second, contrary to the first result, CSA adoption results in higher consumption expenditure per year than its combination with non-farm employment (the option that characterizes labour-oriented households), and the wealthiest households earn more on average than the poorest by adopting the two strategies. The labour demand effect could explain our results because CSA and non-farm employment compete for productive household labour. However, taking account of seasonality would help to establish such relationships because farm-oriented households that adopt CSA would engage in non-farm employment or migrate during the off-season when labour demand for farming is at its low.

Overall, our results suggest that, in a country such as Ethiopia, where markets are not complete and institutions are lacking, the adoption of CSA significantly improves rural households' welfare. Most of the CSA practices we have considered in this study (e.g., zero tillage, natural fertilizer, and other soil fertility management practices) are adopted by households in the lower segment of the income distribution, indicating that they are likely to be adopted by poor rural households. There could, however, be other factors that constrain the adoption of CSA that would lead to suboptimal adoption of CSA. Policies that seek to leverage the welfare benefits of CSA need to acknowledge the capacity of households in CSA adoption and non-farm employment.

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Appendix A

Table A1. Descriptive statistics by adoption status.

	Non-Adoptors				CSA				Non-Farm				Both			
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Multidimensionally poor	0.521	0.500	0	1	0.523	0.500	0	1	0.469	0.500	0	1	0.289	0.454	0	1
Yearly household consumption per adult equivalent	13,223.100	11,977.800	311	169,992	13,314.850	12,457.250	817	126,687	13,892.390	11,078.550	273	124,959	18,010.810	12,548.540	1299	206,891
Monetary poor	0.440	0.497	0	1	0.405	0.491	0	1	0.350	0.478	0	1	0.254	0.436	0	1
Gender of household head (Male = 1)	0.798	0.401	0	1	0.738	0.440	0	1	0.779	0.415	0	1	0.689	0.464	0	1
Household head age	46.312	15.727	15	97	45.439	15.490	17	97	42.931	13.636	17	85	35.577	11.814	18	85
Household size	4.860	2.106	1	13	5.009	2.304	1	14	5.173	2.216	1	19	4.075	2.283	1	11
Household head attended any school (yes = 1)	0.391	0.488	0	1	0.226	0.419	0	1	0.450	0.498	0	1	0.583	0.494	0	1
TLU	3.163	3.058	0	49	3.003	6.154	0	40	2.644	2.504	0	19	1.333	2.951	0	37
Land size in hectares	1.108	1.252	0	25	0.895	4.769	0	200	1.011	1.053	0	18	0.617	1.196	0	6
Distance to the nearest Road (in KM)	17.731	16.736	0	81	29.419	39.138	0	313	17.401	18.248	0	81	25.121	46.018	0	312
Distance to the nearest market (in KM)	67.043	44.162	0	295	107.085	84.665	0	452	74.016	46.956	2	237	85.966	75.550	1	451
Access to extension service (1 = yes)	0.458	0.498	0	1	0.227	0.419	0	1	0.489	0.500	0	1	0.257	0.439	0	1
HH experience Increase in price of inputs (1 = yes)	0.074	0.261	0	1	0.064	0.245	0	1	0.070	0.256	0	1	0.053	0.225	0	1
Temperature$_{t-3}$ (°C)	26.244	3.070	19	36	29.110	4.104	19	37	26.493	2.854	19	35	27.595	4.055	19	37
Precipitation$_{t-3}$ (mm)	104.878	30.109	13	179	78.862	32.198	13	178	106.107	29.510	15	179	91.681	38.339	13	178
Tigray	0.067	0.250	0	1	0.039	0.194	0	1	0.077	0.266	0	1	0.108	0.311	0	1
Afar	0.002	0.042	0	1	0.034	0.182	0	1	0.001	0.034	0	1	0.023	0.152	0	1
Amhara	0.271	0.445	0	1	0.259	0.438	0	1	0.228	0.420	0	1	0.327	0.470	0	1
Somali	0.002	0.040	0	1	0.215	0.411	0	1	0.000	0.000	0	0	0.119	0.324	0	1
Benishg	0.012	0.110	0	1	0.004	0.060	0	1	0.010	0.100	0	1	0.004	0.062	0	1
Snnpr	0.241	0.428	0	1	0.089	0.285	0	1	0.302	0.460	0	1	0.071	0.258	0	1
Gambella	0.004	0.062	0	1	0.001	0.030	0	1	0.003	0.056	0	1	0.005	0.071	0	1
Harari	0.002	0.047	0	1	0.001	0.028	0	1	0.002	0.047	0	1	0.003	0.055	0	1
Diredawa	0.002	0.043	0	1	0.003	0.055	0	1	0.001	0.035	0	1	0.007	0.082	0	1
SPI	0.241	0.530	−1	2	0.340	0.615	−1	2	0.140	0.481	−1	1	0.210	0.501	−1	2
N		1549				815				408				298		

Table A2. First stage regression: Multinomial logistic regression.

	CSA		Non-Farm Employment		Both	
	Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Male headed household	0.138 **	0.214	−0.369	0.149	0.131	0.300
Household head age	−0.013 **	0.006	−0.013 **	0.004	−0.014 *	0.009
Household size	−0.031	0.042	0.105 ***	0.029	0.057	0.056
Household head has formal education	−0.584 **	0.205	0.347 ***	0.130	0.394	0.261
Livestock owned (TLUs)	0.027	0.022	−0.092 ***	0.025	0.006	0.029
Land size (ha)	−0.232 **	0.095	0.040	0.041	−0.233 *	0.139
Distance to the nearest road (Km)	0.002	0.006	−0.005	0.004	−0.009	0.009
Distance to the nearest market (Km)	0.004 *	0.002	0.002	0.002	0.000	0.003
Access to extension service	−0.809 ***	0.196	0.204 *	0.120	−1.241 ***	0.327
HH experienced increase in price of inputs	−0.143	0.327	−0.071	0.234	−0.405	0.528
Temperature$_{t-3}$ (°C)	0.014	0.032	0.018	0.024	0.013	0.048
Precipitation$_{t-3}$ (mm)	0.000	0.005	0.001	0.003	0.003	0.008
Region: Oromia is reference						
Tigray	−0.990 *	0.539	0.242	0.391	0.285	0.859
Afar	0.314	0.540	−0.303	0.577	0.636	0.819
Amhara	−0.119	0.375	0.114	0.260	0.749	0.641
Benishangul	0.071	0.508	−0.380	0.309	0.239	0.908
SNNPR	−0.058	0.366	0.049	0.213	−0.293	0.675
Gambella	−1.563 **	0.752	−0.352	0.353	−0.496	0.849
Harari	−0.582	0.607	0.239	0.374	1.087	0.854
Dire Dawa	−0.388	0.505	−0.169	0.439	0.177	0.805
Village CSA adoption (exc the HH)	0.557 ***	0.036	0.052	0.035	0.601 ***	0.051
Standardized Precipitation Index (SPI)	−0.205	0.224	−0.172	0.186	−0.432	0.318
Deviation of lagged Temperature from 5 year average	−0.988	1.583	0.643	1.222	0.037	2.454
Constant	−2.823 ***	1.152	−1.734 **	0.833	−4.908 **	1.693
Log likelihood			−1823.238			
$\chi_2(d.o.f)$			1527.89			
p-value			0.000			
N			2480			

Untreated is the base outcome. Both refers to CSA and non-farm employment. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A3. Second stage regression: Selectivity correction based on multinomial logit.

Outcome: Consumption Expenditure per Adult per Year	Untreated		CSA		Non-Farm Employment		Both	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Male headed household	−647.794	1407.587	1864.387	1689.594	5494.745	5429.676	496.665	9439.629
Household head age	21.547 ***	44.655	24.705	42.585	83.903	176.948	−55.137	214.753
Household size	−1569.439	381.989	−2644.005 ***	404.438	−3367.261	1885.380	−3900.255	2170.416
Household head has formal education	−13.438	1266.101	−2427.447	4771.329	−2244.021	4708.002	628.959	11,857.720
Livestock owned (TLUs)	−72.966	234.418	109.454	82.895	1465.730	1229.869	72.692	237.829
Land size (ha)	1077.980 *	450.633	58.883	629.946	−347.509	1051.076	1085.144	2756.769
Distance to the nearest road (Km)	6.234	31.635	−15.722	55.641	20.066	103.261	−157.388	209.932
Distance to the nearest market (Km)	−17.105	13.622	−14.913	20.121	−28.419	37.620	84.182	54.346
Access to extension service	1541.917	1188.651	7288.972 *	3525.309	−5567.906	2864.401	2568.609	7722.111
HH experience increase in price of inputs	1630.208	1913.848	2629.312	2815.814	3059.396	4651.715	−7827.601	16,930.300
Temperature $_{t-3}$ (°C)	−352.074	176.029	−37.557	228.969	−318.039	405.817	288.024	1081.100
Precipitation$_{t-3}$ (mm)	−31.095 *	19.487	−79.495	52.132	−29.607	51.669	−20.956	130.833
Tigray	−4981.706 **	1758.475	−13,728.530 *	5827.003	−3866.661	9008.290	−2036.716	13,400.070
Afar	268.887	3091.796	−4445.513	3718.047	6695.543	6955.002	−1377.425	11,706.560
Amhara	−6805.383 ***	1289.746	−8320.415 *	3453.741	−4426.591	4632.513	−5631.169	10,844.490
Benishangul	1595.048	2558.396	−7962.553	5107.872	6408.502	7016.610	−9257.664	12,430.730
SNNPR	1251.305	1477.770	−5649.447	4510.612	−264.617	2702.248	586.654	11,754.390
Gambella	−398.819	1952.055	15,279.600	15,132.130	−3700.723	4974.234	1468.541	19,261.650
Harari	1664.206	2314.187	−14,412.500 *	7224.393	6572.607	4181.652	13,677.790	22,832.050
Dire Dawa	1469.473	3361.643	−5746.686	3938.873	−442.420	6943.445	6424.720	18,852.370
Constant	37,630.900 ***	3875.059	28,631.140 *	12,257.180	96,470.850	60,709.180	66,523.680	61,090.560
ρ_0	−0.271	0.239	0.924	0.520	2.641	1.813	−0.044	1.087
ρ_1	0.452	0.587	0.343	0.286	2.081 *	0.954	1.106	1.295
ρ_2	0.593	0.853	−1.576	0.944	−0.412	0.568	1.985	1.235
ρ_3	−2.256 ***	0.607	−1.232	1.067	−0.373	1.331	−0.218	0.345
Log likelihood				−1823.238				
$\chi_2(d.o.f)$				1527.89				
p-value				0.000				
N				2480				

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A4. Second stage regression: Selectivity correction based on multinomial logit.

Outcome: Monetary Poverty	Untreated		CSA		Non-Farm Employment		Both	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Male headed household	0.036	0.079	−0.125	0.070	−0.072	0.107	0.369 *	0.148
Household head age	0.002	0.002	0.000	0.002	0.001	0.004	0.001	0.005
Household size	0.048 ***	0.014	0.105 ***	0.019	0.077 *	0.032	0.021	0.031
Household head has formal education	−0.139	0.077	0.016	0.173	−0.106	0.128	−0.186	0.381
Livestock owned (TLUs)	0.013	0.009	−0.001	0.006	−0.011	0.027	0.004	0.013
Land size (ha)	−0.043 ***	0.015	−0.071 *	0.031	−0.013	0.025	−0.039	0.070
Distance to the nearest road (Km)	0.001	0.001	0.001	0.002	0.003	0.002	0.022 **	0.007
Distance to the nearest market (Km)	0.000	0.000	−0.001	0.001	0.000	0.001	−0.004	0.002
Access to extension service	−0.123 ***	0.047	−0.142	0.106	0.033	0.083	−0.258	0.241
HH experience increase in price of inputs	0.002	0.063	−0.201	0.108	−0.170 *	0.080	0.263	0.225
Temperature $_{t-3}$ (°C)	0.019 *	0.008	0.019	0.012	0.005	0.009	−0.014	0.027
Precipitation$_{t-3}$ (mm)	−0.001	0.001	−0.002	0.002	0.000	0.002	−0.004	0.004
Tigray	0.083	0.072	0.106	0.201	0.252	0.162	0.053	0.423
Afar	0.139	0.136	−0.031	0.147	−0.194	0.212	−0.067	0.316
Amhara	0.290 ***	0.072	0.352 *	0.142	0.206 **	0.065	0.059	0.329
Benishangul	0.034	0.075	0.140	0.198	0.025	0.162	0.249	0.384
SNNPR	0.156 *	0.077	0.346 *	0.142	0.143	0.105	0.295	0.430
Gambella	0.133	0.109	0.052	0.316	0.208	0.126	0.137	0.540
Harari	−0.046	0.079	0.148	0.282	−0.078	0.114	−0.150	0.511
Dire Dawa	−0.067	0.121	0.016	0.185	0.528 **	0.197	0.287	0.330
Constant	−0.792	0.248	−0.205	0.498	−0.171	1.445	−0.998	2.365
ρ_0	0.006	0.277	−0.567	0.603	−0.297	1.473	−0.407	0.871
ρ_1	−0.280	0.546	−0.401	0.222	−1.040	1.035	−1.006	1.384
ρ_2	−1.721 *	0.726	−0.700	0.978	−0.421	0.568	−2.414 *	0.959
ρ_3	0.092	0.758	1.603	1.113	−0.315	1.177	−0.090	0.387
Log likelihood				−1823.238				
$\chi_2(d.o.f)$				1527.89				
p-value				0.000				
N				2480				

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A5. Second stage regression: Selectivity correction based on multinomial logit.

Outcome: Multidimensional Poverty	Untreated		CSA		Non-Farm Work		Both	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Male headed household	0.028	0.049	−0.159 **	0.072	0.023	0.131	0.328	0.163
Household head age	0.002	0.002	0.002	0.003	0.005	0.004	0.004	0.004
Household size	0.051 ***	0.009	0.112 ***	0.018	0.058 *	0.031	0.052	0.035
Household head has formal education	−0.133 *	0.055	0.101	0.117	−0.164 *	0.119	0.047	0.325
Livestock owned (TLUs)	0.010	0.008	−0.004	0.006	0.005	0.021	−0.002	0.009
Land size (ha)	−0.042 *	0.018	0.000	0.032	−0.025	0.021	0.032	0.093
Distance to the nearest road (Km)	0.001	0.001	0.001	0.002	0.005	0.002	0.019 **	0.006
Distance to the nearest market (Km)	0.000	0.000	0.000	0.001	−0.001	0.001	−0.003 *	0.002
Access to extension service	−0.099	0.038	−0.178	0.114	−0.030	0.096	−0.264	0.299
HH experience increase in price of inputs	0.020	0.061	−0.288 *	0.101	−0.240 *	0.129	0.170	0.242
Temperature$_{t-3}$ (°C)	0.019 **	0.006	0.021	0.012	0.001	0.013	−0.008	0.028
Precipitation$_{t-3}$ (mm)	0.000	0.001	0.000	0.002	0.000	0.002	0.001	0.003
Tigray	0.131 *	0.068	0.150	0.255	0.068	0.147	0.409	0.466
Afar	0.112	0.146	−0.017	0.142	−0.284	0.210	0.195	0.360
Amhara	0.301 ***	0.045	0.412 ***	0.121	0.194	0.090	0.158	0.271
Benishangul	0.041	0.082	0.106	0.241	0.025	0.170	0.070	0.529
SNNPR	0.130 **	0.066	0.244	0.141	0.027	0.116	0.101	0.344
Gambella	0.184	0.129	−0.069	0.236	0.133	0.180	0.531	0.545
Harari	−0.070	0.057	0.377	0.256	−0.203	0.160	0.248	0.367
Dire Dawa	0.048	0.060	0.026	0.194	0.475 **	0.211	0.676	0.412
Constant	−0.817	0.218	−0.471	0.503	0.582	1.173	−3.621 *	1.927
ρ_0	−0.052	0.265	−0.706	0.586	0.061	1.114	−0.810	0.631
ρ_1	−0.379	0.428	−0.306	0.243	−1.164	0.778	−1.885 *	0.812
ρ_2	−1.728 ***	0.488	0.686	1.158	−0.882	0.493	−2.007	1.138
ρ_3	0.106	0.812	1.522	0.961	0.468	1.050	0.066	0.307
Log likelihood				−1823.238				
$\chi_2(d.o.f)$				1527.89				
P−value				0.000				
N				2480				

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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