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Determinants of Adoption and Impacts of Sustainable Land Management and Climate Smart Agricultural Practices (SLM-CSA)

Panel Data Evidence from the Ethiopian Highlands

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Determinants of Adoption and Impacts of Sustainable Land Management and Climate Smart Agricultural Practices (SLM-CSA): Panel Data Evidence from the Ethiopian Highlands

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Abstract

This paper analyzes the factors affecting adoption of sustainable land management and climate smart agricultural (SLM-CSA) practices (in particular tree planting, soil conservation and intercropping) and the effects of adoption on crop net revenue. We use two rounds of household and parcel level survey data collected from the East Gojjam and South Wollo Zones in the Amhara region of Ethiopia, in combination with spatially explicit climate data (rainfall and temperature). We use a multinomial endogenous switching regression model to understand the impacts of SLM-CSA practices on crop net revenue and we conduct a counterfactual analysis to compare the returns from various adaptation strategies. The results show the importance of household characteristics, physical characteristics of the farm, and climate-related factors in farm households' decisions to adopt adaptation strategies. We also find that the adoption of SLM-CSA practices, either in isolation or in combination, can result in both positive and negative returns in crop net revenue. Tree planting has the best payoff among the practices considered in this study, either in isolation or in combination. The study also suggests that adoption of all three SLM-CSA practices does not necessarily result in better returns compared to other strategies considered in this study.

Key Words: Sustainable land management, climate smart, adaptation, climate change, endogenous switching, Ethiopia

JEL Codes: Q16, Q54, Q56

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1. Introduction

Ethiopia's GDP is closely associated with the performance of its smallholder and rain-fed agriculture (Deressa and Hassan 2010), which is characterized by a high degree of land degradation. Climate change is anticipated to further accelerate land degradation. With limited diversification of the economy and reliance on rain-fed agriculture, Ethiopia's development prospects have been closely associated with climate. According to the World Bank (2006), catastrophic hydrological events such as droughts and floods have reduced Ethiopia's economic growth by more than a third. The frequency of droughts has increased over the past few decades, especially in the lowlands (NMS 2007). A study by NMS (2007) highlighted that annual minimum temperature has been increasing by about 0.37 degrees Celsius every 10 years over the past 55 years in Ethiopia. Rainfall has been more erratic, with some areas becoming drier and others becoming wetter. These findings point out that climatic variation and climate change have already happened in this part of the world. The prospect of further climate change can exacerbate this very difficult situation. As a result of these changes in climate, the identification of effective adaptation strategies is of paramount importance in order to support the yields of food crops and improve the livelihood of smallholders.

Therefore, this study aims at identifying the factors that affect the adoption of sustainable land management and climate smart agricultural (SLM-CSA) adaptation

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* Abebe D. Beyene, corresponding author, Environment and Climate Research Center, Ethiopian Development Research Institute, email: abebed2002@yahoo.co.uk. Alemu Mekonnen, Department of Economics, Addis Ababa University, email: alemu_m2004@yahoo.com. Menale Kassie, International Center of Insect Physiology and Ecology (ICIPE), P.O. Box 1041, 00621 Village, Market, Nairobi, Kenya, email: mkassie@icipe.org. Salvatore Di Falco, University of Geneva, Switzerland, email: Salvatore.DiFalco@unige.ch. Mintewab Bezabih Ayele, Environment and Climate Research Center, Ethiopian Development Research Institute. email: mintewab.ayele@gmail.com.

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practices, in particular tree planting, physical soil conservation measures and intercropping with leguminous crops. It also evaluates the impacts of combinations of SLM-CSA adaptation strategies on crop net revenue in smallholder farming systems. These strategies can indeed buffer against the impacts of climate change and play an important role in reducing the food insecurity of farm households. We use two rounds of data collected in 2005 and 2007 to understand the adoption process and impact of the three sustainable land management and climate smart agricultural adaptation practices, individually or in combination, in two zones of the Amhara region.

With regard to the wider literature, understanding of joint adoption of a combination of adaptation practices and their economic implications is still quite weak (Di Falco and Veronesi 2013). Adaptation is a complex phenomenon comprising different practices that may play an important role in reducing the food insecurity of farm households. There are different measures that, in principle, farmers can adopt as complements, substitutes or supplements to address climate change and other overlapping production constraints.

Sustainable Land Management (SLM) can be defined as any intervention that is aimed at sustaining or restoring the productive capacity of land, including cropland, rangeland, and forested land, to deliver public and private goods (FAO 2009). In agriculture, sustainable land management refers to the maintenance over time of soil productivity, which requires a combination of soil fertility treatment (application of mineral and organic fertilizers to the soil) with soil and water conservation measures (implementation of agronomic, soil management and physical measures) (FAO 2009). Appropriate land management practices that allow communities to better adapt to climate change will also often contribute to mitigating climate change. Many SLM practices can contribute to sequestering carbon in soils and vegetation, reducing emissions of greenhouse gases (carbon dioxide, methane and nitrous oxide) and reducing the use of fossil fuel and agrochemicals. Climate Smart Agricultural (CSA) practices are practices that sustainably increase productivity, enhance resilience, reduce/remove GHGs, and enhance achievement of national food security and development goals (FAO 2010). A number of initiatives related to CSA are being carried out in Ethiopia. These initiatives promote and train farmers in appropriate methods of fertilizer application, composting, crop rotation and intercropping (FAO 2016). Also, both SLM and CSA practices can offer smallholders the opportunity to reduce the need for resources such as labour, capital, etc. By recognizing multiple benefits of both SLM and CSA practices, we want to investigate the potential role of a combination of sustainable land management and climate smart agricultural (SLM-CSA) practices as an adaptation strategy.

The premise of this research is that one way to understand the role of adaptation is to study farmers' responses to the impacts of climate change to date. Adaptation to changing climatic conditions is not, in fact, a new process. Farmers have constantly implemented adjustments to cope with the vagaries of climatic conditions. Thus, understanding the impacts of past adaptation can help gauge the importance of these strategies in the face of future climate change. In addition, a farm-level perspective can be particularly useful to inform us of the barriers and drivers behind adaptation strategies. Of special interest is the role of SLM-CSA in this process. Therefore, this research contributes to sustainability and poverty reduction, as SLM-CSA practices can enable farmers to become resilient to climate change by improving ecosystem services and functions, increasing agricultural productivity and enhancing food security. In addition, the findings of this study can help policy makers implement Ethiopia's Climate Resilient Green Economy strategy (CRGE). Such practices can also help mitigate climate change. Another contribution of this study is that, unlike most other related studies which use cross-sectional data (see, for example, Teklewold et al. 2013; DiFalco and Veronesi 2013), it uses panel data and addresses the dynamic aspects of the problem.

The rest of the paper is organized as follows. Section 2 presents a brief review of related studies. Section 3 provides a brief description of the data. Section 4 presents the conceptual and econometric framework employed in this study. Discussion of empirical results is presented in Section 5. The final section concludes and draws key findings and policy implications.

2. Previous Research

The links between climate change and crop productivity have largely been explored focusing on the relationship between climate variables and agriculture. Linking the different sustainable land management practices to adaptation and mitigation strategies is still an area on which researchers need to focus. Nkonya et al. (2011) examine the impact of government policies on adaptation to climate change by taking cases from Kenya and Uganda in East Africa and Niger and Nigeria in West Africa. They find that, while there is a high level of awareness of climate change and a reasonable level of awareness and adoption of sustainable land and water management (SLWM) practices, the actual use of SLWM for climate change adaptation and mitigation is so far very limited. Their findings also show that, in all the countries considered, there are success stories with regard to the influence of policies on the adoption of the different practices as well as response to climate change. They argue that public investment to raise awareness and providing technological support are necessary to scale up those practices.

Bryan et al. (2011) analyzes the synergies and tradeoffs among climate change adaptation, mitigation, and productivity/profitability. They use survey data to assess common land management practices (including application of inorganic fertilizer, composting or manure, intercropping, soil bunds, crop residue management and grass strips), climate change adaptation options, mitigation options for crops and livestock simulated by modeling tools, and productivity/profitability impacts calculated based on survey data. They find that farmers in Kenya do not fully recognize the inter-linkages between agricultural productivity, adaptation, and mitigation. However, efforts to consider the impact of all available types of management will be complex and difficult to understand. A recent study by Teklewold et al. (2017), using a multinomial endogenous switching regression model, analyzes whether a combination of multiple climate-smart practices is more resilient against climate change. They find that current choices of alternative combinations of climate smart practices (agricultural water management, improved crop seeds and fertilizer) and related farm income in the Nile basin of Ethiopia are heavily influenced by climate – specifically, by heat, rainfall, and rainfall variability. Other studies also qualitatively indicate the link between agriculture and climate change (e.g., FAO 2016; Vasconcelos et al. 2013). Deressa and Hassan (2010) and DiFalco et al. (2011) focus on the impact of climate change on crop production and hence food security. Seo and Mendelsohn (2008) look at the livestock sector and climate change. Rigorous quantitative empirical evidence to better understand the link between SLM-CSA practices and climate change is still inadequate.

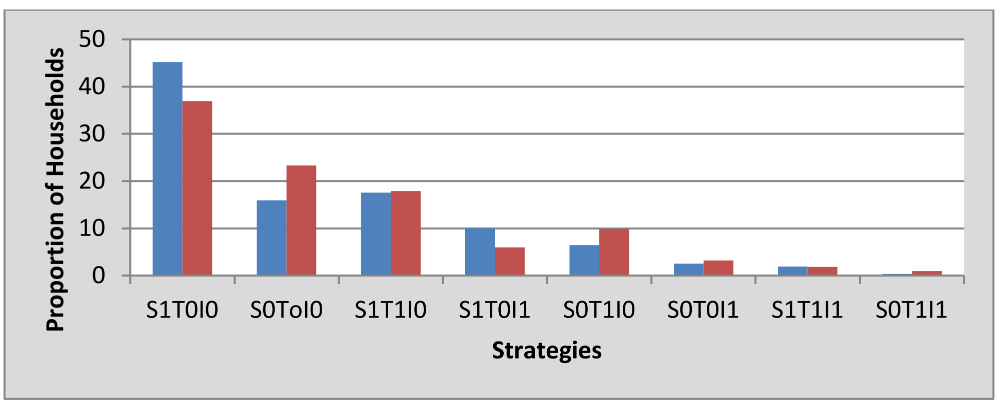
Different approaches have been employed to examine the links between climate change and crop food productivity. There is, indeed, a large and growing body of literature that uses either agronomic models or Ricardian analysis to investigate the magnitude of these impacts (e.g., Deressa and Hassan 2010; Kurukulasuriya and Rosenthal 2003; Seo and Mendelsohn 2008). Agronomic models attempt to estimate directly, through crop models, the impacts of climate change on crop yields. They rely on experimental findings that indicate changes in yield of staple food crops (such as wheat) as a consequence of warming temperatures (e.g., Amthor 2001; Fuhrer 2003; Gregory et al. 1999). Then, the results from the model are fed into behavioural models that simulate the impact of different agronomic practices on farm income or welfare. The Ricardian approach (pioneered by Mendelsohn et al. 1994) purports to isolate, through econometric analysis of cross-sectional data, the effects of climate on farm income and land value, after controlling for other relevant explanatory variables (e.g., factor endowment, and proximity to markets). The Ricardian approach implicitly incorporates the possibility of the implementation of adaptation strategies by farmers. Based on the assumption that farmers have been adapting optimally to climate over time, the regression coefficients incorporate farmers' adaptive response when estimating the marginal impacts on outputs of future temperature or rainfall changes. Thus, the Ricardian approach holds that adaptation choices do not need to be modeled explicitly because they have been efficiently implemented. One of the obvious shortcomings of this approach is that it is a "black box" that fails to identify the key adaptation strategies that reduce the effects of climate on food production (Di Falco et al. 2011). Disentangling the productive implications of different adaptation strategies to climate change is of paramount importance. Furthermore, the most relevant impact studies of adaptation strategies have long focused on a single adaptation practice (e.g., Di Falco et al. 2011; Di Falco et al. 2012), even though farmers adopt more than one practice to address their overlapping constraints Most empirical studies on factors influencing adaptation strategies also do not consider the interaction among different adaptation practices (e.g., Deressa and Hassan 2010). Recognizing the inter-relationships among adaptation practices while analyzing adoption decisions is important to obtain consistent estimates of the impacts of adaptation strategies. Modeling adoption and impact analysis of adaptation strategies in a multiple adaptation choice framework is therefore important in order to capture useful economic information contained in interdependent and simultaneous adoption decisions. In addition to using a more appropriate empirical methodology, which has been applied only by a few studies, this study uses panel data, unlike other studies of which we are aware. This study also adds to the existing literature on climate change and agriculture in Africa by examining the nexus between climate change and agricultural practices that are considered to be sustainable land management and climate smart practices.

3. Variables and Data Description

Data used in this analysis were taken from the Sustainable Land Management Survey in the central highlands of Ethiopia, conducted by the Environmental Economics Policy Forum for Ethiopia. The survey involved 1,760 farm households randomly selected from 14 villages, located in two zones of the Amhara National Regional State of Ethiopia, in two waves (in the years 2005 and 2007). The dataset includes detailed quantitative and qualitative information on the socioeconomic characteristics of households, physical characteristics of their farms, social capital indicators, land tenure and land use, and sustainable land management practices. Rainfall and temperature data from eight meteorological stations close to the survey villages were also obtained from the Ethiopian Meteorology Agency. Finally, given that micro-climate is a critical factor in farm household decision making, farm-level climate data is a more precise measure of the impacts of climate change at farm level. Accordingly, unlike many previous studies that use village-level climate variables, we employ farm-level climate change measures in our analysis; these are generated based on an inverse distance weighing interpolation technique.[1] Following Deschenes and Greenstone (2007), we use degree days based daily temperature values.[2] The resulting degree day temperature values and precipitation measures are used to construct the climate related variables.

The SLM-CSA practices considered in this study are soil conservation, tree planting, and intercropping with leguminous crops. We need to first estimate the determinants of the adoption of combinations of the SLM-CSA practices. The dependent variables for this analysis are the different combinations of the three SLM-CSA practices considered.

Figure 1. Proportion of Sample Households Adapting SLM-CSA Practices by Year



Note: Subscript 1 refers to adoption and 0 otherwise. S, T, and I stand for soil conservation, tree planting and intercropping, respectively. Red is for year 2005 and blue is for 2007.

[1] Except for Di Falco and Bulte (2011), we are not aware of micro-level climate variables used in such studies.

[2] Most previous studies have calculated degree days based on monthly temperature (e.g., Schlenker et al. 2006).

The farmers practice different types of soil conservation measures (denoted by S) such as traditional and modern terraces (both with rock and soil), contour farming, digging ditches, and grass cover. So, we consider whether the farmer has practiced any kind of soil and water conservation activities.[3] T, which represents 'Tree planting', is constructed by asking the household whether there are any kinds of trees, including permanent crops, on its parcel. Intercropping (I) is considered to have taken place if the farmer has grown leguminous crops such as horse beans (*bakela*), cow peas (*ater*), soya beans (*akuri ater*), lentils (*misir*), *adenguare*, *guaya* (vetch), haricot beans (*boloke*), chick peas (*shimbra*), Lupinus albus (*gibto*), *nug*, sesame (*selit*), or linseed (*telba*). Legumes enrich the soil with nitrogen via their unique ability to fix atmospheric N_2 in symbiosis with the soil bacteria rhizobia, and they also increase soil carbon content, both of which enhance crop productivity (Jensen et al. 2012. Furthermore, they have an important role in mitigating climate change, in two ways: the nitrogen fixing process means that less energy input is required to manufacture chemical fertilizers, and they accelerate carbon sequestration in soil (Jensen et al. 2012). Therefore, legumes should be an important part of the Ethiopian government's strategy to promote sustainable agricultural practices.

Thus, we denote soil conservation, tree planting and intercropping by S, T and I, respectively. When a practice is adopted, we use 1; when it is not, we use 0. A total of 8 (=2*x*2*x*2) combinations are possible: $S_1T_1I_1$ (adoption of all three practices), $S_1T_1I_0$ (soil conservation and tree planting), $S_1T_0I_0$ (soil conservation), $S_1T_0I_1$ (soil conservation and intercropping), $S_0T_0I_0$ (no adoption), $S_0T_0I_1$ (only intercropping), $S_0T_1I_1$(intercropping and tree planting), and $S_0T_1I_0$ (only tree planting). We will refer to S, T and I as *practices* and to each of the eight possible combinations as *strategies*.

4. Analytical and Econometric Framework

In this section, we specify a model of climate change adaptation and net revenues in the setting of a two-stage framework following Di Falco and Veronesi (2013) and Teklewold et al. (2013). Our analysis is based on a random utility framework to model multiple adaptation practices and impacts of various combinations of these practices. In the first stage, we assume that farm households face a choice of *M* interrelated practices to respond to long-term changes in mean temperature and rainfall. In the second stage, we

[3] A separate analysis for each type of soil conservation practice would give a better idea as to which type of conservation is best for the farmer. However, the small number of observations did not allow us to conduct such an analysis.

outline the econometric model that is used to investigate the impacts of adaptation strategies on crop net revenues. Crop net revenues are calculated by taking the difference between the revenue that can be obtained from all crop production and the costs or expenses of variable inputs incurred in producing those crops, such as fertilizer, chemical and improved seeds.

4.1. Multinomial Endogenous Switching Regression Model

In the first stage, farmers' choice of combinations of adaptation practices is modeled using a multinomial logit selection model, while recognizing the inter-relationships among the choices.

Let *A** be the latent variable that captures the expected net revenues from implementing strategy *j* (*j = 1 … M*) with respect to implementing any other strategy *k*. We specify the latent variable as

$$A^*_{itj} = \overline{V}_{itj} + \eta_{itj} = Z_{it}\alpha_j + \eta_{itj} \tag{1}$$

$$A_{it} = \begin{cases} 1 \;\; iff \;\; A^*_{it1} \succ \max\limits_{k \neq 1}\left(A^*_{itk}\right) or \; \eta_{it1} \prec 0 \\ \vdots \\ M \;\; iff \;\; A^*_{itM} \succ \max\limits_{k \neq M}\left(A^*_{itk}\right) or \; \eta_{itM} \prec 0 \end{cases}$$

that is, farm household *i* will choose strategy *j* in response to long-term changes in mean temperature and rainfall if strategy *j* provides expected net revenues greater than any other strategy $k \neq j$, i.e., if $\varepsilon_{itj} = \max\limits_{k \neq j}\left(A^*_{itk} - A^*_{itj}\right) \prec 0$.

Equation (1) includes a deterministic component ($\overline{V}_{itj} = Z_{it}\alpha_j$) and an idiosyncratic unobserved stochastic component η_{itj} . The latter captures all the variables that are relevant to the farm household's decision maker but are unknown to the researcher, such as skills or motivation. It can be interpreted as the unobserved individual propensity to adapt.

The deterministic component $\overline{V}_{itj}$ depends on factors Z_{it} that affect the likelihood of choosing strategy *j*. These variables include the farm household's characteristics (e.g., age, gender, education, and family size), assets such as livestock, farm (parcel) characteristics (e.g., soil fertility and slope), past climatic factors (e.g., 1970 – 2000 mean rainfall and temperature), and households' experience of previous extreme weather events such as droughts, floods, and hailstorms. Furthermore, social capital indicators, such as the number of relatives and trust in people, are included. We also examine the impact on adoption of access to government extension, which is the main source of information for farmers.

It is assumed that the covariate vector Z_{it} is uncorrelated with the idiosyncratic unobserved stochastic component η_{itj}, i.e., $E(\eta_{itj}/Z_{it})=0$. Under the assumption that η_{itj} are independent and identically Gumbel distributed, that is, under the Independence of Irrelevant Alternatives (IIA) hypothesis, selection model (1) leads to a multinomial logit model (McFadden 1973) where the probability of choosing strategy j (P_{itj}) is

$$P_{itj} = P(\varepsilon_{itj} \prec 0 \mid Z_i) = \frac{\exp(Z_{it}\alpha_j)}{\sum_{k=1}^{M}\exp(Z_{it}\alpha_k)} \quad (2)$$

In the second stage of the estimation, the impacts of each combination of adaptation practices on the outcome variable (i.e., net revenue) are evaluated using ordinary least squares (OLS) with a selectivity correction term from the first stage. Our model implies that farm households face a total of *M* regimes (one regime per strategy, where *j=1* is the reference category "non-adapting").

We have a net revenue equation for each possible regime *j* defined as:

(3a) Regime 1: $y_{it1} = X_{it}\beta_1 + \mu_{it1} \; if \quad A_{it} = 1$

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(3m) Regime M: $y_{itM} = X_{it}\beta_M + \mu_{itM} \; if \quad A_{it} = M$

where y_{itj} is the net revenue of farm household *i* in regime *j*, (*j = 1, … ,M*), and X_{it} represents a vector of inputs (e.g., fertilizers and manure), household head's and farm household's characteristics, soil characteristics, and the past climatic factors included in Z_{it}; u_{itj} represents the unobserved stochastic component, which verifies $E(u_{itj} \mid X_{it}, Z_{it}) = 0$ and $V(u_{itj} \mid X_{it}, Z_{it}) = \sigma_j^2$. For each sample observation, only one among the *M* dependent variables (net revenues) is observed. When estimating an OLS model, the net revenues Equations (3*a*)-(3*m*) are estimated separately. However, if the error terms of the selection model (1) η_{itj} are correlated with the error terms u_{itj} of the net revenue functions (3*a*)-(3*m*), the expected values of u_{itj} conditional on the sample selection are nonzero, and the OLS estimates will be inconsistent. To correct for the potential inconsistency, we employ the model by Bourguignon et al. (2007), which takes into account the correlation between the error terms η_{itj} from the multinomial logit model estimated in the first stage and the error terms from each net revenue equation u_{itj}. We refer to this model as a multinomial endogenous switching regression model, following the terminology of Maddala and Nelson (1975), extended to the multinomial case. The model by Bourguignon et al. (2007) shows that consistent estimates of β_j in the outcome Equations (3*a*)-(3*m*) can be obtained by estimating selection bias-corrected net revenues equations.[4]

4.2. Analysis of Treatment Effects

In this section, we specify and discuss how we can find the effect of adoption of SLM-CSA practice *j* on the net revenues of the farm households that adopted strategy *j*. We employ the multinomial endogenous switching regression model to produce selection-corrected predictions of counterfactual net revenues. This is because unobserved heterogeneity (e.g., ability, motivation) in the propensity to choose an adaptation strategy also affects net revenues and creates a selection bias in the net revenue equation (the derivation is found in Appendix B).

5. Discussion of Results

The descriptive statistics for the explanatory variables included in the analysis are shown in Table 1.

First, we discuss the factors affecting the adoption of a combination of practices, and then the impacts of adoption of the various adaptation strategies on farm net revenue.

[4] A detailed description of this model is presented in Appendix B.

Table 1. Descriptive Statistics of Explanatory Variables Used in the Empirical Analysis

Variables	2007 Mean	2007 S.D.	2005 Mean	2005 S.D.	T test (t-values)
Sex of head (=1 if male)	0.84	0.36	0.85	0.35	-2.12
Age of head in years	50.89	14.46	50.10	15.10	3.45
Marital status (=1 if married)	0.83	0.37	0.85	0.36	-2.88
Head can read and write (=1 if yes)	0.37	0.48	0.42	0.49	-6.07***
Family size in adult equivalent	6.78	2.388	6.439	2.300	9.48***
Livestock in Tropical Livestock Units (TLU)	4.36	3.15	4.20	3.04	3.36***
Slope of parcel(=1 ifflat, 0 otherwise)	0.72	0.45	0.68	0.47	6.56***
Soil Quality (=1 if *lem* and 0 otherwise)	0.53	0.50	0.44	0.50	11.49***
Parcel distance in walking minutes	18.01	19.38	15.69	31.67	5.72***
Distance to the nearest town in minutes	71.40	51.71	68.50	50.66	3.65
Long term average annual rainfall in mm	1134.50	247.12	1133.99	258.23	0.13
Long term annual temperature in ^{0}C	464.94	159.89	466.84	152.65	0.77
Shock occurrence in the past two years(=1 if yes)	0.49	0.50	0.63	0.48	-17.51***
Extension visit(=1 if the hh contacted the agent in the past year)	0.25	0.43	0.48	0.50	-31.15***
Number of relatives	19.18	20.45	10.85	13.75	30.70***
Trust in people (yes=1, 0 otherwise)	0.45	0.50	0.71	0.46	35.84***
Amount of manure in kg	1685.72	2215.18	1670.10	2204.75	0.46
Amount of fertilizer in kg	321.87	582.47	339.51	590.77	-1.95
Land tenure security(=1 if the parcel has legal certificate)	0.80	0.40	0.83	0.37	-4.68

5.1. Determinants of Adaptation Strategies

In this section, we present the factors that affect the probability of adopting sustainable land management and climate smart agricultural practices in response to climate change. Table 2 presents estimation results from the multinomial logit model, which allows us to identify the main determinants of adoption of adaptation practices in combination or in isolation.

In order to identify the model, we need to find appropriate instruments which can be included in the selection equation but not in the outcome equation. Though it is difficult to satisfy the exclusion restriction, we need to argue intuitively and look for variables that directly affect the selection variable but not the outcome variable. Similar to Di Falco and Veronesi (2013), we use as selection instruments in the net revenue functions the variables related to past experience of extreme weather events or shocks (e.g., droughts, floods, pests and crop diseases), and the main information sources (i.e., government extension). In addition, indicators of social capital such as the number of relatives and trust in people are included in the selection equation. We believe that these social capital indicators influence adoption of better agricultural and climate practices (e.g., Wossen et al. 2015; Willy and Holm-Muller 2013; Isham 2002) but may not have a direct effect on net revenue per hectare. We conducted simple falsification tests to check the validity of these instruments. A valid instrument affects the decision of choosing an adaptation strategy, but will not affect the net revenue per hectare among farm households that did not adapt (Di Falco et al. 2011). We find that the instruments are jointly significant in the decision to adopt most of the strategies but they are jointly not significant in affecting the net revenue per hectare.[5] Standard errors are bootstrapped to account for the heteroskedasticity arising from the two-stage estimation procedure.

The presence of correlation between unobserved household fixed effects and observed covariates confirms the need to follow Mundlak's approach. The F test reported at the bottom of Table 2 shows that the null hypothesis that all coefficients of the mean of time-varying covariates are jointly statistically equal to zero is rejected in most of the equations.

The estimation results show different effects of variables on the different adaptation strategies. Asset ownership such as livestock is significant and positively correlated with the decision to adopt the following adaptation strategies: soil conservation, soil conservation and tree planting, soil conservation and intercropping, and a combination of all three strategies. Asset rich households may have the necessary resources to take appropriate adaptation measures.

The role of household characteristics was examined by including sex, age, marital status and education of household head, and family size. Male-headed households are more likely to adopt soil conservation in conjunction with intercropping. In order to capture the lifecycle effect of age, we included the square of the age of the household head. The result shows that age is negatively correlated with the probability of adoption of most of the strategies, except intercropping in isolation, but the result for intercropping is not significant. As the household gets older, the probability of adopting climate adaptation strategies declines, showing that younger household heads are more likely to adopt these strategies. Other household characteristics such as household size and marital status are positively and significantly correlated with the probability of adopting intercropping alone and in combination with tree planting. As expected, literate households are more likely to adopt soil conservation in conjunction with tree planting. Similarly, adoption of tree planting alone is positively affected if the head is literate.

[5] The estimates used to check the validity of the instruments are found in Appendix A, Table A3.

Table 2. Parameter Estimates of the Multinomial Logit Model

Variables	Soil conservation and tree planting ($S_1T_1I_0$)2		Soil conservation only 3($S_1T_0I_0$)		Soil conservation and intercropping 4($S_1T_0I_1$)		Soil conservation and tree planting and intercropping 5(S1T1I1)		Intercropping ($S_0T_0I_1$) 6		Tree planting and intercropping ($S_0T_1I_1$) 7		Tree planting ($S_0T_1I_0$) 8	
	coff	S.E.	coff	S.E.	coff	S.E.	coff	S.E.	coff	S.E.	coff	S.E.	coff	S.E.
Sex of household head	-0.122	0.130	0.121	0.105	0.508***	0.173	0.422	0.281	-0.278	0.226	-0.296	0.457	-0.128	0.169
Age of household head	0.039***	0.014	0.020*	0.011	0.040**	0.017	0.007	0.029	-0.007	0.024	0.096*	0.053	0.013	0.017
Age square	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000	-0.000	0.000	0.000	0.000	-0.001*	0.000	-0.000	0.000
Household size	-0.025	0.077	0.069	0.061	-0.032	0.097	0.083	0.191	0.410***	0.147	0.585*	0.307	0.076	0.103
Marital status	0.105	0.129	-0.033	0.105	-0.020	0.163	0.113	0.257	0.496**	0.232	0.901*	0.518	0.070	0.164
Head is literate	0.200***	0.072	0.037	0.058	-0.046	0.088	0.168	0.142	-0.009	0.124	0.056	0.257	0.152*	0.092
Slope of parcel	-0.688***	0.071	-0.172***	0.058	-0.278***	0.088	-0.842***	0.145	-0.125	0.130	-0.660***	0.224	-0.338***	0.093
Soil Quality	0.316***	0.067	0.054	0.054	0.039	0.084	0.234	0.144	0.144	0.120	-0.052	0.244	0.343***	0.084
Parcel distance	-0.645***	0.028	-0.016	0.022	-0.001	0.033	-0.621***	0.060	0.052	0.044	-0.786***	0.104	-0.581***	0.036
Livestock	0.432***	0.142	0.447***	0.111	0.649***	0.171	0.889**	0.355	0.273	0.237	-0.032	0.422	0.005	0.169
Distance to town	0.022	0.038	0.039	0.032	0.095*	0.049	0.049	0.089	0.090	0.073	0.210	0.159	-0.069	0.044
Manure	0.046***	0.014	0.024**	0.011	0.050***	0.016	0.000	0.028	-0.018	0.021	0.018	0.044	-0.014	0.016
Fertilizer	0.019	0.025	0.059***	0.020	0.045	0.033	0.092	0.063	0.107**	0.053	0.098	0.107	-0.033	0.029
Rainfall	-0.043	0.116	-0.045	0.097	-0.104	0.111	-0.240*	0.143	-0.105	0.206	-0.339	0.297	1.003**	0.415
Temperature	-6.022	21.253	-0.368*	0.203	-14.367	23.062	-0.996**	0.462	-62.352	41.362	-194.726***	52.290	-0.441	0.293
Square of rainfall	-0.000	0.000	-0.000	0.000	-0.000	0.000	0.000	0.000	-0.000	0.000	0.000	0.001	-0.002***	0.001
Square of temperature	0.014	0.044	0.003	0.003	0.036	0.049	0.006	0.007	0.135	0.089	0.412***	0.111	0.008	0.005

Table 2. Parameter Estimates of the Multinomial Logit Model (continued)

Variables	Soil conservation and tree planting($S_1T_1I_0$)2		Soil conservation only 3($S_1T_0I_0$)		Soil conservation and intercropping 4($S_1T_0I_1$)		Soil conservation and tree planting and intercropping 5(S_1T1I1)		Intercropping($S_0T_0I_1$) 6		Tree planting and intercropping($S_0T_1I_1$) 7		Tree planting ($S_0T_1I_0$) 8	
	coff	S.E.	coff	S.E.	coff	S.E.	coff	S.E.	coff	S.E.	coff	S.E.	coff	S.E.
Land tenure security	-0.012	0.083	-0.192***	0.065	-0.223**	0.102	0.052	0.188	-0.081	0.147	0.692*	0.398	-0.280***	0.096
Year dummy	0.215***	0.075	0.667***	0.061	1.189***	0.092	0.286*	0.164	0.532***	0.124	-0.638**	0.319	-0.184*	0.099
Selection instruments														
Shock occurrence	0.285***	0.063	0.211***	0.051	0.221***	0.078	0.303**	0.133	0.100	0.109	-0.057	0.223	0.013	0.079
Extension visit	0.144**	0.069	0.311***	0.056	0.030	0.083	0.098	0.143	-0.073	0.121	-0.102	0.261	-0.007	0.087
Number of relatives	0.002	0.002	0.002	0.002	-0.001	0.002	-0.006	0.004	-0.010***	0.004	-0.007	0.009	-0.005*	0.003
Trust people	0.097	0.064	-0.143***	0.051	-0.102	0.080	0.278**	0.141	-0.099	0.109	-0.053	0.225	0.010	0.080
Mundlak's variables														
Mean livestock	-0.395**	0.154	-0.366***	0.121	-0.420**	0.186	-0.757**	0.366	0.368	0.261	0.128	0.476	0.127	0.182
Mean hh size	-0.011	0.078	-0.130**	0.062	-0.034	0.098	-0.119	0.194	-0.468***	0.148	-0.571*	0.320	-0.116	0.104
Mean manure	0.021	0.019	0.028*	0.015	0.028	0.022	0.072*	0.040	0.006	0.031	-0.011	0.061	0.037*	0.021
Mean fertilizer	0.075***	0.028	0.038*	0.023	0.085**	0.035	0.045	0.066	-0.059	0.059	-0.274**	0.121	0.039	0.033
Constant	33.285	121.180	0.921	1.039	75.421	131.317	1.599	1.882	349.951	235.221	1,103.019***	297.626	-3.586*	2.110
Joint significance of time varying covariates χ2 (4)	12.78**		18.5***		10.78**		7.64		12.56**		11.81**		6.47	
Joint significance of selection instruments χ2 (4)	31.74***		57.01***		10.07**		12.80**		9.72**		1.18		3.33	
Observations	13,880		13,880		13,880		13,880		13,880		13,880		13,880	

Note: District dummies were included but not reported for the sake of economizing space. *p <0.10, ** p <0.05, *** p <0.01. Analysis of the joint significance of location variables χ2 (7) was also conducted and found that they are jointly significant in all cases. The base category is 'No adaptation"; that is, the category $S_0T_0I_0$. The sample size is 13,880. Robust standard errors are in parentheses.

The variables livestock, distance of parcel, distance to town, amount of manure, amount of fertilizer, temperature and rainfall are in log form. For description of variables, including their measurement, please see Column 1 of Table 1.

Climate-related variables have different effects on the adoption of SLM-CSA practices in combination or in isolation, suggesting that these strategies are adopted in response to climate change. Adoption of tree planting has a quadratic relationship with precipitation, in that adoption of tree planting is likely to decrease as the amount of precipitation increases. We also find that, in areas where temperature is higher, farm households are more likely to adopt tree planting combined with intercropping ($S_0T_1I_1$). This is in line with the study by Teklewold et al. (2017), who found that the probability of adopting a combination of improved seeds and water management practices and a combination of fertilizer and water management practices increases in higher-temperature areas.

Parcel characteristics, such as soil quality, slope of parcel and distance of parcel from the homestead, are included in the analysis. If the slope is flat (*medama*), then the probability of adopting sustainable land management practices decreases, except for intercropping, which is not statistically significant. This shows that those households with hilly and rugged lands are more likely to adopt adaptive strategies. This result is not surprising, because farms which are not flat are more vulnerable to erosion and loss of fertility. On the other hand, soil quality is not a significant factor for the adoption of most of the strategies. Good soil quality positively and significantly affects the probability of adoption of SLM-CSA strategies such as tree planting and a combination of tree planting and soil conservation. As expected, it is less likely that farmers will adopt most of the strategies on distant parcels. Specifically, adaptation strategies such as tree planting, intercropping together with tree planting, the combination of all three strategies, and soil conservation in conjunction with tree planting are less likely to be practiced on parcels which are far from the farmer’s residence. This might be due to the difficulty of monitoring by farmers. In general, the physical characteristics as well as the location of farms matter in the adoption decision of various kinds of adaptation strategies by farm households.

Similar to the findings of the existing literature, which documents the importance of extension services in the adoption of agricultural technologies in general and climate adaptation strategies in particular, we found that access to extension is positively and significantly correlated with the adoption of soil conservation alone and soil conservation in combination with tree planting. DiFalco and Veronesi (2013) also found that access to extension services is positively and significantly correlated with the probability of adaptation via changing crops in isolation and in conjunction with soil conservation measures. However, we find that whether the farmer had contact with extension is not significant for the probability of adopting other adaptation practices, either in isolation or in combination. Similarly, a study by Teklewold et al. (2017) finds that whether the farmer has been in contact with extension services has no impact on adoption of fertilizer and improved seeds; those authors suggest that the quality of extension services, not just contact with extension agents, is important for adoption decisions.

We also analyzed the role of social capital, represented here by the number of relatives in and outside of the farmer's village and whether the farmer has trust in people living in the villages. As shown in Table 2, we found mixed results. Trust in people is negatively correlated with the probability of adaptation via soil conservation in isolation, but positively and significantly correlated with the adoption of soil conservation measures, tree planting and intercropping in combination. On the other hand, intercropping in isolation and tree planting in isolation are negatively correlated with the number of relatives the farmer has in and outside of the farmer's village. Similarly, Beyene and Kassie (2015) find that the speed of adoption of improved maize variety in Tanzania is negatively correlated with the number of relatives on whom the household can rely in times of critical need. This supports the hypothesis that social networks may hinder the technology adoption process under certain circumstances (DiFalco and Bulte 2011).

The occurrence of a shock in the past two years is positively correlated with adoption of adaptation practices in combination, specifically soil conservation and tree planting, soil conservation and intercropping, and a combination of the three strategies. The probability of adopting soil conservation alone is higher if the household has experienced a shock in the past two years. This variable is not significant in the adoption of other strategies such as intercropping, tree planting and a combination of the two.[6]

5.3. Estimation of the Treatment Effects

Here, our objective is to identify the strategies that offer higher net revenue per hectare. The simplest approach is to look at the actual mean net revenues per hectare by farm household adaptation strategy. This shows that adoption of intercropping and tree planting in combination will yield the highest return (2474 Birr[7]/ha). Another option is to check the effect of each adaptation strategy on net revenue. Appendix A presents the

[6] The role of the various types of shocks can be analyzed separately, which might have different effects on farmers' adaptation decisions.

[7] At the time of the survey, the exchange rate was 8-9 Ethiopian Birr to US $1.00.

impact of adopting various combinations of practices on net revenue (random effect estimates are presented). Almost all combinations (except adoption of tree planting only, $S_0T_1I_0$) do have a positive and significant effect on net revenue. Under this simple approach, adoption of intercropping only ($S_0T_0I_1$) has a larger effect on net revenue than any other strategy (see Appendix, Table A1).

The problem with the above estimation methods is that they are simple comparisons that do not account for both observed and unobserved factors that may influence net revenue. The difference in net revenues may be caused by unobservable characteristics of the farm households, such as their skills. Therefore, the next step is to estimate the impact of adopting various combinations of SLM-CSA choices on net revenue by using a counterfactual analysis. We follow the approach discussed in Section 4.2. This will help us identify the strategies yielding the highest revenues.[8] Table 3 presents net revenues per hectare under actual and counterfactual conditions.

Table 3. The Effect of Combination of SLM-CSA Practices on Net Revenue Per Hectare

Strategies	Description	Actual revenues (Birr/Ha)	Counterfactual (Birr/Ha)	Impact (Birr/Ha)
$S_1T_1I_0$(2)	Soil conservation and Tree planting	1559.31	1272.113	287.1965***
		(18.67172)	(15.97915)	(24.46047)
$S_1T_0I_0$ (3)	Soil conservation only	1065.02	1166.723	-101.7022***
		(9.465151)	(13.02854)	(16.32766)
$S_1T_0I_1$ (4)	Soil conservation and Intercropping	2214.409	2146.941	67.46605*
		(30.01089)	(24.88356)	(42.76877)
$S_1T_1I_1$ (5)	Soil conservation and Tree planting and Intercropping	2308.416	1719.312	589.1071***
		(80.96913)	(36.91307)	(117.6478)
$S_0T_0I_1$ (6)	Intercropping only	2156.444	1586.161	570.2829***
		(104.161)	(43.37291)	(116.687)
$S_0T_1I_1$ (7)	Intercropping and Tree Planting	2473.88	2361.194	112.6857
		(282.512)	(64.24835)	(344.0342)
$S_0T_1I_0$ (8)	Tree Planting Only	1736.02	1134.289	601.731***
		(35.36169)	(23.87748)	(43.5972)

Note: Figures in parentheses are standard errors; *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

[8] The second-stage regression estimates reported in Appendix 2 show that many of the selection correction terms are significant at least at the 10% level. This suggests that adoption of SLM-CSA practices would not have the same effect on non-adopters should they choose to adopt.

We compare expected net revenues under the actual case that the farm household adopted a particular strategy to adapt to climate change and the counterfactual case that the farmer did not adopt that strategy. The last column of Table 3 presents the impact of each adaptation strategy on net revenue, which is the treatment effect, calculated as the difference between Columns (1) and (2) based on Equations (5a—5m) and (6a-6m), as shown in Appendix B.

The result shows that adaptation strategies yield both positive and negative returns, but the magnitude differs depending on the strategy. The impact of the strategy 'Soil conservation and tree planting' is 288 Birr per ha, which is the lowest of all the strategies with a positive and significant return. The highest payoff, 602 Birr/ha, is when tree planting is adopted in isolation. In percentage terms, tree planting alone increases net return by 53%, followed by adoption of the combination of the three practices, which increases net revenue by almost 34%. This result suggests that, unless other justifications are considered, tree planting alone would enhance farmers' livelihood more than other strategies considered in this study, in combination or isolation. For instance, the impact of adoption of intercropping only is 570 Birr/ha. In other words, intercropping alone ceases to dominate as a strategy when the counterfactual approach is applied.

Surprisingly, implementing soil conservation alone reduces the net revenue/ha from 1166 Birr/ha to 1065 Birr/ha, which is a reduction of net revenue per hectare by 8.7%. This might be due to the nature and timing of the investment. Soil conservation is a long-term investment and the return may take up to seven years (Schimidt and Tadesse 2014). If the investment was made shortly before this survey was conducted, the return may not be positive. However, further investigation is necessary before we make a strong conclusion. For example, as described earlier, separate consideration by type of soil conservation might be better than taking soil conservation as a whole.

Unlike the findings of other studies such as Teklewold et al. (2017), we find that adopting all three strategies simultaneously does not guarantee the maximum return. While Teklewold et al. (2017) considered a different combination of practices (agricultural water management, improved crop seeds and fertilizer), our results lead us to caution against the conclusion that multiple adoption is always the best strategy. It is possible that making multiple changes, relative to making one or two changes at a time, places burdens on farmers in terms of risk, expenditures, etc.

Our findings are similar to those of DiFalco and Veronesi (2013), who found that a combination of two strategies (soil conservation and changing crop varieties) yielded better return than adoption of three strategies (changing crops, water conservation, and soil conservation) in rural Ethiopia.[9] Our findings indicate that the payoff from combinations of strategies depends on the type of strategies considered in the analysis, as there is a possibility that a single strategy may yield a better return than combinations of practices.

6. Conclusion

This paper investigates the driving forces behind farm households' decisions to adapt to climate change and examines the economic implications of adopting one or a combination of SLM-CSA strategies. Panel data collected in the highlands of Ethiopia in the years 2005 and 2007 were used for the empirical analysis. Climate indicators such as rainfall and temperature and household socioeconomic indicators were included. A multinomial endogenous switching regression model was employed to identify the determinants of adoption of SLM-CSA strategies and the various factors affecting the net revenues under each regime. By employing this model, we take into account heterogeneity in the decision to adopt a combination of strategies (as opposed to a single strategy), as well as unobservable characteristics of farmers and farms such as microclimatic differences.

The econometric result shows that several variables are important in influencing the decision to adopt the adaptation strategies considered in this study. Variables such as household characteristics are important in the decision to adopt a combination of adaptive practices. For example, the decision to adopt SLM-CSA practices is positively correlated with households with younger heads, large family size, and literate household heads. Parcel characteristics such as soil quality, distance of parcel, slope of parcel, and climate variables (rainfall and temperature) have different effects on the probability of adopting the SLM-CSA practices considered in this study. The occurrence of shocks and extension visits are also positively correlated with some, but not all, of the combinations of practices. Policy makers and relevant stakeholders working on improving the livelihood of farm households may use this information in order to influence the adoption of various SLM-CSA practices.

These results imply that policies aiming to improve the livelihood of smallholder farmers should consider the importance of adopting those SLM-CSA practices that yield

[9] Though the return from any other combinations of two strategies is higher, the difference is not statistically significant.

the highest return. More complex strategies such as simultaneous adoption of soil conservation, tree planting and intercropping will not always yield the highest return. The highest payoff is when tree planting is adopted in isolation, at 602 Birr/ha, followed by adoption of a combination of the three strategies i.e., soil conservation and tree planting and intercropping, which is 589 Birr/ha. This shows that it is necessary to identify the right combinations of agricultural practices to enhance farm income and improve the livelihood of farmers. Other socioeconomic and institutional factors should be considered in order to find appropriate intervention mechanisms for adopting the best adaptation practices. For example, education could help to promote tree planting. Households with a greater number of livestock are more likely to adopt various adaptation strategies. Different effects of variables on different adaptation strategies suggest the need for different interventions.

Future studies may focus on a survey with more waves to better capture the dynamic aspects of the problems and the benefits of climate change adaptation strategies. The role of other adaptation strategies and interactions among them need to be studied in order to come up with a comprehensive strategy that enhances farmers' welfare by reducing the negative impacts of climate change and land degradation.

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Appendix A

Table A1. The Effect of Combinations of Strategies on Net Revenue (Random Effect Estimates)

Variables	Coef.	Robust Std. Err.	Z	P>z
Sex of head	-5.530	37.977	-0.150	0.884
Age of head	-30.589	2.719	-11.250	0.000
Age square	0.188	0.004	51.830	0.000
Household size	-189.204	100.922	-1.870	0.061
Marital status	-40.844	46.222	-0.880	0.377
Head is literate	155.762	54.833	2.840	0.005
Slope of parcel	281.779	116.812	2.410	0.016
Soil quality	236.194	48.019	4.920	0.000
Parcel distance	-112.512	123.948	-0.910	0.364
Land tenure security	-227.414	27.030	-8.410	0.000
Livestock	-313.880	272.790	-1.150	0.250
Distance to town	-83.770	35.329	-2.370	0.018
Rainfall	-50.541	135.331	-0.370	0.709
Temperature	-216.616	125.804	-1.720	0.085
Square of rainfall('000)	0.094	0.254	0.370	0.712
Square of temperature('000)	2.501	5.620	0.450	0.656
Manure	9.365	6.525	1.440	0.151
Fertilizer	59.106	45.806	1.290	0.197
Year dummy	-566.998	40.646	-13.950	0.000
Mundlak's variables				
Mean livestock	451.969	334.885	1.350	0.177
Mean of household size	192.800	92.676	2.080	0.037
Mean of manure	-27.906	61.537	-0.450	0.650
Mean of fertilizer	-78.087	47.848	-1.630	0.103
Adaptation Strategies				
Soil conservation, tree planting and intercropping	397.797	126.142	3.150	0.002
Soil conservation and tree planting	85.698	42.996	1.990	0.046
Soil conservation only	-65.566	31.189	-2.100	0.036
Soil conservation and intercropping	648.517	186.101	3.480	0.000
Intercropping	1162.332	67.250	17.280	0.000
Tree planting and intercropping	649.723	154.293	4.210	0.000
Tree planting only	249.527	350.187	0.710	0.476
Constant	3429.263	838.922	4.090	0.000

Note: Distance to parcel, distance to town, manure, fertilizer, livestock, rainfall and temperature are all in log form. Dependent variable is net revenue per hectare. Fixed effects at the *woreda* level are included but not reported. (The woreda is the second-lowest administrative level or district in Ethiopia.) Robust standard errors are reported.

Table A2. Estimates of Net Revenue Equations using Multinomial Endogenous Switching Regression Model

Variables	No Adaptation	$S_1T_1I_0$	$S_1T_0I_0$	$S_1T_0I_1$	S_1T1I1	$S_0T_0I_1$	$S_0T_1I_1$	$S_0T_1I_0$
Sex of head	8157.43***	19611.96***	3368.91*	-17172.59*	27227.80*	-4860.45	6593.37	21880.53***
	(2608.95)	(3163.42)	(1951.98)	(9443.12)	(16502.66)	(11504.48)	(46338.51)	(4994.05)
age of head	159.48	370.95**	-168.44	-957.55*	-556.26	-1299.45	792.40	111.48
	(191.53)	(144.41)	(137.94)	(503.63)	(1536.37)	(808.85)	(2415.07)	(272.19)
Agesquare	-1.60	-3.64***	1.32	8.55*	4.72	11.34	-6.39	-1.13
	(1.72)	(1.29)	(1.23)	(4.54)	(13.83)	(7.29)	(21.70)	(2.48)
Family size	-1717.95***	-2197.27***	-72.67	2465.21	-2224.31	2629.23	792.28	-4155.16***
	(479.06)	(600.57)	(367.02)	(1526.49)	(3607.30)	(2040.82)	(7734.60)	(1019.96)
MaritalStatus	-2093.52***	-5137.46***	-334.59	4419.06*	-7350.87	2792.10	-756.29	-6452.70***
	(599.08)	(1010.42)	(555.90)	(2516.10)	(6418.63)	(3334.24)	(14419.17)	(1776.50)
Head is literate	-1055.18	-3377.97***	-1359.11**	1752.97	-8728.89*	-2264.80	1432.62	-4275.06***
	(894.64)	(919.59)	(575.38)	(2341.42)	(5077.70)	(3007.34)	(14103.45)	(1227.13)
Slope of parcel	-313.15	301.38	2491.73**	5632.05	10961.58	10775.31*	-1996.60	2652.35
	(1852.87)	(1530.76)	(1248.32)	(4544.67)	(12885.11)	(6542.25)	(24344.86)	(2159.32)
SoilQuality	-2132.05	-6455.16***	-3038.77***	2717.19	-16290.10	-4828.68	-2635.26	-7621.31***
	(1861.27)	(1793.20)	(1158.64)	(4901.43)	(10247.74)	(5587.18)	(27055.05)	(2414.13)
Parceldistance	1401.41	5233.66*	5397.10**	4375.48	24590.28	16960.08	-3251.67	7934.18*
	(3503.09)	(3006.18)	(2286.06)	(8423.85)	(22920.87)	(11483.00)	(46413.91)	(4216.72)
Land security	-61.98	1187.61	1942.04**	1154.37	8149.36	1371.85	3057.55	698.14
	(1131.36)	(1068.83)	(792.69)	(2544.57)	(7468.72)	(3055.86)	(16318.37)	(1516.49)
Livestock	4041.85***	8912.68***	2059.24**	-6709.23	12694.60*	-362.24	3358.15	9456.49***
	(1409.66)	(1608.51)	(926.32)	(4593.15)	(6976.20)	(5604.58)	(23684.39)	(2531.67)
Distance to town	553.87	1770.70***	750.92**	-870.92	3985.74	1208.16	2080.60	1618.24**
	(482.28)	(437.67)	(300.68)	(1207.31)	(2485.01)	(1379.55)	(6599.12)	(645.71)
Rainfall	-1849.52	-9015.82**	-8735.55***	-7123.44	-37854.11	-22471.81	681.65	-9290.68
	(5027.33)	(4256.84)	(3301.19)	(11799.02)	(33909.45)	(16238.18)	(66899.00)	(6427.52)
Temperature	-5672.36	-10093.63***	5553.15*	24491.12**	13213.51	26936.00	-12589.88	-10462.53*
	(4403.99)	(3598.19)	(3374.28)	(11703.16)	(37181.69)	(19616.02)	(49551.61)	(5618.37)
Square of rainfall	2.83	14.16*	14.87***	13.67	66.01	40.23	1.07	14.82
	(8.82)	(7.42)	(5.75)	(20.50)	(59.50)	(28.40)	(116.99)	(10.92)
Square of Temperature	46.87	79.17**	-51.59*	-186.40*	-105.50	-228.35	63.39	82.62
	(38.86)	(33.47)	(30.01)	(100.64)	(318.38)	(187.33)	(570.77)	(55.25)
Amount of manure	178.35*	367.14***	10.33	-472.90*	49.27	-441.52	213.49	329.98
	(96.54)	(77.27)	(69.65)	(247.75)	(614.09)	(402.15)	(1330.22)	(207.28)
Amount of fertilizer	159.88	701.37**	761.63***	406.28	2512.29	1953.35*	-210.72	591.08
	(368.85)	(313.50)	(256.50)	(910.77)	(2627.02)	(1166.15)	(4740.39)	(455.11)
Year dummy	4794.94**	12022.84***	3358.10**	-7346.47	21418.67*	6111.99	804.81	14640.55***
	(2281.84)	(2512.64)	(1390.13)	(6898.62)	(11953.48)	(8393.77)	(37272.55)	(3956.50)

Mundlak variables								
Mean of livestock	-5702.12***	-12508.51***	-2015.25	11398.92*	-14583.53	6325.18	-5317.93	-13166.31***
	(1972.78)	(2093.99)	(1318.05)	(6541.34)	(10516.98)	(8010.12)	(30988.53)	(3395.92)
Mean of family size	1660.55***	2272.49***	246.68	-2143.06	2866.94	-2335.78	-1121.77	4321.44***
	(470.06)	(591.43)	(328.10)	(1458.01)	(3034.98)	(1902.54)	(7775.56)	(1010.31)
Mean of manure	281.51**	659.94***	-79.31	-1021.85**	-115.70	-1075.55	106.77	542.72**
	(131.33)	(138.98)	(108.03)	(439.78)	(1248.91)	(706.66)	(1927.75)	(228.06)
Mean of fertilizer	245.73	19.31	-530.82**	-523.12	-1126.18	-1349.26*	198.42	256.76
	(267.61)	(248.93)	(210.38)	(680.75)	(1982.38)	(809.41)	(3707.13)	(399.94)
Selection bias correction terms								
millsp1	-196.90	-1026.79	-1794.22**	-2738.49	-9117.98	-5201.55	578.31	-2464.99*
	(1282.09)	(1103.54)	(846.17)	(3144.77)	(8512.69)	(4190.37)	(16368.72)	(1424.99)
millsp2	2675.29***	6468.99***	1441.88**	-5829.24*	8935.11*	-303.69	2388.85	7106.43***
	(996.80)	(1085.74)	(681.21)	(3321.02)	(5155.34)	(3985.14)	(17286.01)	(1741.39)
millsp3	-1.10	-761.05***	-239.91*	868.05*	-368.82	-57.04	-76.98	398.43
	(283.20)	(212.34)	(144.65)	(472.55)	(1115.69)	(822.88)	(2882.96)	(415.74)
millsp4	-2567.98***	-5391.56***	-437.55	5855.04**	-4748.63	2992.49	-2862.93	-6306.41***
	(791.62)	(871.65)	(620.38)	(2882.66)	(6077.79)	(3826.44)	(11786.26)	(1440.15)
millsp5	-1464.07**	-3710.21***	-1027.83***	2565.35	-5786.23*	18.04	-1647.64	-4010.58***
	(640.00)	(640.87)	(383.30)	(1818.39)	(3111.89)	(2152.73)	(10296.45)	(1041.80)
millsp6	2007.28**	4271.79***	-125.97	-5930.74**	1783.83	-5275.26	3286.47	4128.76***
	(781.70)	(745.00)	(665.78)	(2613.11)	(6828.19)	(3761.33)	(11051.91)	(1253.83)
millsp7	-414.23*	-1289.99***	-33.98	1883.56**	-371.14	1732.82	-1242.56	-658.90
	(234.33)	(196.01)	(195.14)	(750.90)	(1857.74)	(1184.80)	(4579.03)	(470.71)
millsp8	145.44	1747.40	2601.57**	3433.85	10714.26	7068.46	-1206.50	2055.71
	(1548.25)	(1289.22)	(1052.90)	(3664.61)	(10970.59)	(4901.22)	(19341.06)	(1715.18)
chi2	2.37e+03	3.03e+03	7.11e+03	.	926.67570	1.66e+03	.	3.04e+03
N	2714	2499	5571	1165	281	429	97	1116

Note: Mills(i) refers to the correction term described in Equation 4a. Fixed effects at the woreda/district level are included. Bootstrapped standard errors are in parentheses.*, **, *** denote level of significance at the 10%, 5%, and 1% level, respectively.The variables livestock, distance of parcel, distance to town, amount of manure, amount of fertilizer, temperature and rainfall are in log form.

Table A3. Parameter Estimates—Test on the Validity of the Selection Instruments

Variables	Coef.	Robust Std. Err.	z	P>z
Sex of head	-207.059	148.868	-1.390	0.164
Age of head	-31.796	33.572	-0.950	0.344
Agesquare	0.188	0.290	0.650	0.517
Household Size	-268.380	258.848	-1.040	0.300
Marital Status	405.753	145.821	2.780	0.005
Head is literate	143.719	180.338	0.800	0.425
Slope of parcel	-85.348	143.355	-0.600	0.552
Landsecurity	-57.561	28.485	-2.020	0.043
Soil Quality	183.363	41.205	4.450	0.000
Parceldistance	-122.942	65.124	-1.890	0.059
Livestock	134.710	78.055	1.730	0.084
Distance to town	-5.017	132.230	-0.040	0.970
Amount of rainfall	2.188	22.308	0.100	0.922
Temperature	-211.746	69.410	-3.050	0.002
Square of rainfall	0.129	0.146	0.880	0.378
Square of temperature	3.314	1.732	1.910	0.056
Manure	8.813	19.468	0.450	0.651
Fertilizer	66.625	47.481	1.400	0.161
Year dummy	-387.334	108.641	-3.570	0.000
Mundlak's variables				
Mean of Livestock	-40.128	40.608	-0.990	0.323
Mean of Household size	231.799	259.963	0.890	0.373
Mean of manure	-31.873	25.979	-1.230	0.220
Mean of fertilizer	-32.821	13.568	-2.420	0.016
Selection Instruments				
Shock occurrence	-53.206	147.278	-0.360	0.718
Extension visit	86.407	23.538	3.670	0.000
Number of relatives	2.100	4.366	0.480	0.631
Trust in people	-104.161	16.935	-6.150	0.000
_cons	2343.417	1989.924	1.180	0.239
Observation		14031		

*, **, *** denote level of significance at the 10%, 5%, and 1% level, respectively. Fixed effects at the woreda/district level are included but not reported. The variables livestock, distance of parcel, distance to town, amount of manure, amount of fertilizer, temperature and rainfall are in log form. Robust standard errors are reported.

Appendix B

According to Bourguignon et al. (2007), the following selection bias-corrected net revenues equations can be used to get consistent estimates of β_j in the outcome equations discussed in Section 4.1, Equations (3*a*)-(3*m*):

(*4a*) Regime 1: $$y_{it1} = X_{it}\beta_1 + \sigma_1 \left[\rho_1 m(P_{it1}) + \sum_j \rho_j m(P_{itj}) \frac{P_{itj}}{(P_{itj}-1)}\right] + v_{it1} \ if \ A_{it} = 1$$

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(*4m*) Regime M:

$$y_{itM} = X_{it}\beta_M + \sigma_M \left[\rho_M m(P_{itM}) + \sum_j \rho_j m(P_{itj}) \frac{P_{itj}}{(P_{itj}-1)}\right] + v_{itM} \ if \ A_{it} = M$$

where P_{itj} represents the probability that farm household *i* chooses strategy *j* as defined in (2), ρ_j is the correlation between u_{itj} and η_{itj}, and $m(P_{itj}) = \int J(v - \log P_j)g(v)dv$, with $j(\cdot)$ being the inverse transformation for the normal distribution function, *g(.)* the unconditional density for the Gumbel distribution, and $v_{itj} = \eta_{itj} + \log P_{tj}$. This implies that the number of bias correction terms in each equation is equal to the number of multinomial logit choices *M.*[10]

We follow Mundlak (1978) and Wooldridge (2002) to control for unobservable characteristics. We exploit the panel nature of the data, and insert in the net revenues Equations (*4a*)-(*4m*) the average of time-variant variables $\overline{X}_i$ such as livestock, manure, fertilizer, and family size. This approach relies on the assumption that the unobservable characteristics v_{it} are a linear function of the averages of the time-variant explanatory variables $\overline{X}_i$, that is, $v_{it} = \overline{X}_i\pi + \psi_{it}$ with $\psi_{it} \sim IIN(0, \sigma^2_\psi)$ and $E(\psi_{it} / \overline{X}) = 0$, where π is the corresponding vector of coefficients and ψ_{it} is a normal error term uncorrelated with $\overline{X}_i$. For comparison purposes, we have employed the same approach to estimate the effect of the adoption of a combination of strategies on net revenue.

[10] Bourguignon et al. (2007) show that selection bias correction based on the multinomial logit model can provide a fairly good correction for the outcome equation, even when the IIA hypothesis is violated.

Analysis of Treatment Effects

Following Bourguignon et al. (2007), the expected net revenues of farm households that adapted strategy j (where *j* = 2 , . . . , *M)* can be derived as follows:

$$5a)\ E\left(y_{it2}/A_{it}=2\right) = X_{it}\beta_2 + \sigma_2\left[\rho_2 m\left(P_{it2}\right) + \sum_{k\neq 2}\rho_k m\left(P_{itk}\right)\frac{P_{itk}}{\left(P_{itk}-1\right)}\right]$$

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$$5m)\ E\left(y_{itM}/A_{it}=M\right) = X_{it}\beta_M + \sigma_M\left[\rho_M m\left(P_{itM}\right) + \sum_{k=1\ldots M-1}^{M}\rho_k m\left(P_{itk}\right)\frac{P_{itk}}{\left(P_{itk}-1\right)}\right]$$

Then, we derive the expected net revenues of farm households that adopted strategy *j* in the counterfactual hypothetical case that they did not adapt (*j* = 1) as follows:

$$6a)\ E\left(y_{it1}/A_i=2\right) = X_{ti}\beta_1 + \sigma_1\left[\rho_1 m\left(P_{it2}\right) + \rho_2 m\left(P_{it1}\right)\frac{P_{it1}}{\left(P_{it1}-1\right)} + \sum_{k=3---M}^{M}\rho_k m\left(P_{itk}\right)\frac{P_{itk}}{\left(P_{itk}-1\right)}\right]$$

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$$6m)\ E\left(y_{it1}/A_i=M\right) = X_{it}\beta_1 + \sigma_1\left[\rho_1 m\left(P_{itM}\right) + \sum_{k=2\ldots M}^{M}\rho_k m\left(P_{it,k-1}\right)\frac{P_{it,k-1}}{\left(P_{it,k-1}-1\right)}\right]$$

Therefore the difference between Equations 5 and 6 (for example, 5a and 6a or 5m and 6m) will give us the average treatment effect (ATT).