Environment for Development

Discussion Paper Series August 2017 ■ EfD DP 17-01

The Impact of Credit Constraints and Climatic Factors on Choice of Adaptation Strategies

Evidence from Rural Ethiopia

Hailu Elias, Mintewab Bezabih Ayele, and Tadele Ferede

Environment for Development Centers

Central America
Research Program in Economics and Environment for Development in Central America Tropical Agricultural Research and Higher Education Center (CATIE)

Chile
Research Nucleus on Environmental and Natural Resource Economics (NENRE)
Universidad de Concepción

China
Environmental Economics Program in China (EEPC)
Peking University

Colombia
The Research Group on Environmental, Natural Resource and Applied Economics Studies (REES-CEDE), Universidad de los Andes, Colombia

Ethiopia
Environment and Climate Research Center (ECRC)
Ethiopian Development Research Institute (EDRI)

India
Centre for Research on the Economics of Climate, Food, Energy, and Environment, (CECFEE), at Indian Statistical Institute, New Delhi, India

Kenya
School of Economics
University of Nairobi

South Africa
Environmental Economics Policy Research Unit (EPRU)
University of Cape Town

Sweden
Environmental Economics Unit
University of Gothenburg

Tanzania
Environment for Development Tanzania
University of Dar es Salaam

USA (Washington, DC)
Resources for the Future (RFF)

Vietnam
University of Economics
Ho Chi Minh City, Vietnam

The Environment for Development (EfD) initiative is an environmental economics program focused on international research collaboration, policy advice, and academic training. Financial support is provided by the Swedish International Development Cooperation Agency (Sida). Learn more at www.efdinitiative.org or contact info@efdinitiative.org.

The Impact of Credit Constraints and Climatic Factors on Choice of Adaptation Strategies: Evidence from Rural Ethiopia

Hailu Elias, Mintewab Bezabih Ayele, and Tadele Ferede

Abstract

Climate adaptation actions, like any other investment, require financial resources, which are likely to be in short supply in the rural sector in developing countries. This paper assesses the role of credit constraints in the choice of adaptation strategies in settings with severe financial market imperfections. Household-level panel data from selected zones in the highland region of Ethiopia, combined with climate information from the adjacent meteorological stations, is employed in the analysis. We quantify the linkage between different forms of credit constraints and choice of climate adaptation strategies, using a multivariate probit regression model. Credit constrained households are significantly less likely to adopt crop diversification and off-farm employment strategies. While credit access encourages irrigation, soil conservation and tree planting are the least responsive to credit access. These results indicate that the severity of credit constraints depends on both the nature of the credit constraint and the type of adaptation investment.

Key Words: credit constraint, climatic factors, adaptation strategies, multivariate probit, Ethiopia

JEL Codes: C23, G29, Q54, Q12

Contents

The Impact of Credit Constraints and Climatic Factors on Choice of Adaptation Strategies: Evidence from Rural Ethiopia

Hailu Elias, Mintewab Bezabih Ayele, and Tadele Ferede*

1. Introduction

Agrarian economies in low-income developing countries, characterized by an uncertain production environment, are inherently risk-prone (Dercon 2002; Yesuf and Bluffstone 2009). The riskiness of the sector is likely to be exacerbated by the threats of climate change (IPCC 2014; Kurukulasuriya et al. 2006). Identifying the opportunities and constraints associated with effective adaptation strategies is, thus, critical for the performance of the sector and the economy as a whole (Madison 2007; Bryan et al. 2013).

Most of the traditional risk sharing or mitigating strategies, particularly those associated with a wider range of shocks, provide only a partial insurance mechanism (Mogues 2011), have a high opportunity cost, tend to be very localized, and are limited in scope (Dercon 2009). In such settings, credit access tends to act as insurance against income shocks (e.g., Yang and Choi 2007).[1] This implies that credit access can potentially be a key strategy to expand and strengthen risk mitigation instruments, particularly with the increasing threat of climate change. In this paper, we assess how different levels of credit constraints affect participation in climate-adaptive investments/instruments, using panel data from rural Ethiopia.

The literature on the relationship between credit access and shocks attests to the view that financial resources can help the poor harness capabilities needed to be resilient against shocks (Ellis 2000). However, the direct role of access to credit in withstanding climatic shocks and the nature of credit constraints and their differing impacts on specific climate change adaptation strategies is not fully understood.

An in-depth analysis of the role of credit constraints in adaptation in the context of climate change is pertinent for the following reasons. There is a growing literature on the links between climate change and agricultural performance, as well as the impacts of

---

* Mintewab Bezabih Ayele, London School of Economics, corresponding author: mintewab.bezabih@port.ac.uk. Hailu Elias and Tadele Ferede, Addis Ababa University, Ethiopia.

[1] Other financial resources that serve similar purposes include remittances and savings (e.g., Fafchamps et al. 1998) and Jacoby and Skofias 1997). However, the analysis in this paper focuses on credit access.

alternative climate adaptation strategies on productivity in the African context (for example, see Di Falco and Bulte 2011; Di Falco et al. 2011; Di Falco and Veronsi 2014; Adger et al. 2003; Seo and Mendelsohn 2008; Hassan and Nhemachena 2008). In addition, the literature on the determinants of adaptation strategies is also a growing area of research (e.g., Teklewold et al. 2015; Di Falco and Veronsi 2014; Deressa et al. 2009). However, there has been little exploration of the impact of credit constraints on the choice of adaption strategies.[2] Specifically, the choice of adaptation strategies and their likely differing responsiveness to financial constraints has been significantly under-researched, especially within a panel framework.

The rest of the paper is organized as follows. In Section 2, a discussion on climate change, credit constraints and adaptive capacity of farm households is presented. Section 3 discusses climate change and credit access in the context of Ethiopia. The survey strategy and data description are provided in Section 4, while the methodological approach, consisting of the econometric strategy, is discussed in Section 5. Section 6 presents the empirical findings and Section 7 concludes the paper.

2. Key Strategies in Adaptation to Climate Change and the Role of Credit Constraints: A Literature Review

In this section, we review the key climate adaptation tools identified in previous literature, focusing on those that are relevant in the empirical context in this study. We also assess how each tool is potentially linked to credit constraints. We choose credit as a determinant of adaptation strategy because investment decisions and agricultural productivity are greatly impacted by credit market imperfections, as shown conceptually (e.g., Stiglitz and Weiss 1981) and empirically (Guirkinger and Boucher 2008; Ali et al. 2012). However, the specific role of credit constraints with respect to climate adaptation has not been widely explored.[3]

[2] Section 2 presents a detailed review of the literature on the links between credit access and adaptation to climate change, focusing on the responsiveness of key adaptation strategies (that are relevant to the setting of the study and empirical analysis) to credit constraints, and highlighting the gaps in the exisiting literature.

[3] As many adaptation strategies could be considered as investment/disinvestment strategies, the key role of credit in shaping agricultural investment decisions is what makes it a pivotal potential instrument in the choice of adaptation strategies. However, credit/borrowing from formal and informal sources is in some instances seen as a coping strategy by itself (Feder et al. 1985).

The choice of the adaptation strategies for this study is based on Deressa et al. (2009) and Di Falco et al. (2011), who assessed responses of farmers who were asked what measures they have taken in response to perceived changes in temperature and precipitation. Accordingly, we consider the following key strategies as climate adaptation tools: soil conservation and tree planting, off-farm employment, crop diversification, asset depletion, and irrigation.[4]

The first strategy, the adoption of soil conservation technologies, has long been understood as a pivotal tool for enhancing food security for smallholder farmers in Sub-Saharan Africa and increasingly more so as a way of shielding against climate risk (Di Falco and Veronsi 2014; Teklewold et al. 2015). Particular to developing countries, the adoption of soil and water conservation measures is found to be one of the major responses to perceived long-term changes in temperature and rainfall (Deressa et al. 2009; Di Falco and Bulte 2011; Kato et al. 2009).

Notwithstanding their importance in both food security and climate risk mitigation (Kassie et al. 2013), the adoption of soil conservation technologies remains too low (Holden et al. 1998; Holden and Shiferaw 2001). Among the many factors that act as barriers to investment in soil conservation, credit market imperfections (which result in short-term planning horizons) are argued to be strong contributors to making investment in soil conservation unattractive (Holden et al. 1998).

The second strategy is crop diversification and the adoption of seed technology. The strategy has significant potential to help farmers withstand the effects of varying climatic factors by increasing overall productivity of agricultural systems. In addition, diversification reduces the risk of crop loss associated with climatic variability (through spreading out the growing and harvesting of different crops over the course of the year) (Di Falco et al. 2010; Di Falco and Chavas 2009). In some cases, particular seed technologies are also shown to play an effective role in buffering against rainfall variability (e.g., Bezu et al. 2014).

---

[4] It should be noted that asset depletion was also reported as a risk mitigation strategy in the survey that we use in the analysis, but not in the two studies discussed above. We included asset depletion as one of the adaptation strategies. The strategies that we have identified below as adaptation strategies could be understood to be risk mitigation strategies. Further, these adaptation strategies could also be thought of as ex-ante and ex-post risk management strategies, with crop diversification, soil conservation and participation in off-farm employment falling into the first category and asset depletion falling into the second category.

While diversification could be considered a capital-saving strategy, certain crop varieties could require access to capital. In their study of the responsiveness of household crop patterns to changing prices and credit availability, Komarek (2010) finds that significant changes in household cropping patterns could occur with improved access to credit. Similarly, Cavatassi et al. (2012) show the negative impact of credit constraints on the ability to diversify. Credit access also has the tendency to increase farm-level diversity by increasing access to different seed materials; in a resource-poor system, even modern varieties appear to contribute to rather than threaten diversity (Benin et al. 2003).

The third strategy considered in this study, off-farm employment, is also known to act as a buffer against climate change (Deressa et al. 2009; Di Falco et al. 2011; Davies et al. 2013; Eakin 2005). However, off-farm income tends to be more effective as a climate coping strategy because climate shocks are idiosyncratic rather than covariant due to the possible correlation with climate-dependent agricultural incomes (Bank 2005). Participation in off-farm activities tends to be constrained by capital needs, as credit constraints may prevent households from taking up non-agricultural activities (Mcnamara and Weiss 2005; Ito and Kurosaki 2009).

The fourth adaptation strategy considered in this paper is irrigation. The reduction in water availability as a result of climate change (both in terms of quantity and reliability) increases the need for an efficient water management system for agriculture, such as irrigation, particularly in Africa (Vörösmarty et al. 2010). The responsiveness of irrigated and rainfed farms to climatic factors is shown to be significantly different in Africa (e.g., Deressa et al. 2006), South America (Seo and Mendelsohn 2008), and the U.S. (Wanga et al. 2009). It should be noted, however, that irrigation's ability to mitigate water scarcity is limited globally by the overall reduction in water availability (Eliotta et al. 2014).

As with the other strategies, there is evidence of significant links between credit constraints and irrigation. Using data on irrigation wells in India, Fafchamps and Pender (1996) show that the availability of credit can dramatically increase investment in irrigation and that interest-rate subsidization has little impact. In Colombia, credit policies promote private investment in irrigation (Dinar and Keck 1997). However, in their assessment of the determinants of irrigation adoption in the Tigray region of Ethiopia, Gebregziabher et al. (2009) find that access to extension service, as opposed to credit, has a significant impact.

Overall, the literature indicates the relevance of the strategies discussed above as climate adaptation tools. However, the degrees of adaptation effectiveness could be dependent on the adaptation options available to a given set of households, which calls for analysing the joint responsiveness of adaptation strategies to climatic factors. In addition, the stringency of credit constraints could differ depending on the credit demands of a given adaptation strategy. These observations indicate the need to empirically investigate the relationships between the adaptation strategies and credit constraints.

3. Climate Change and Credit Constraints in the Ethiopian Context

Climate models estimate that the median temperature in Africa will increase between 3 and 4^{o}C by the end of the 21st century, which is roughly 1.5 times higher than the global mean response (Bryan et al. 2013). This makes poor African countries such as Ethiopia more vulnerable to the adverse impacts of climate change, particularly given their limited adaptive capacity. In line with this, estimates by FAO (2008) indicate that, by 2100, climate change alone would cause a decline in GDP of Sub-Saharan Africa by about 2 to 7 percent.

Particular to Ethiopia, global circulation models predict an increase in mean temperature of 0.9 to 1.1^{o}C by 2030, 1.7 to 2.1^{o}C by 2050 and 2.7 to 3.4 ^{o}C by 2080 (Belliethathan et al. 2009). Further, Tadege (2007) showed that long-term climate change in Ethiopia is associated with changes in precipitation patterns, rainfall variability, and temperature, which could increase the country’s frequency of droughts and floods. Indeed, Ethiopia is highly susceptible to frequent climate extremes such as disastrous droughts and floods, which have caused significant adverse effects on the country’s economy and society and are expected to become more pronounced in the future under climate change (You and Ringler 2010).

Rainfall variability has particularly contributed to many of the food shortages and crop crises farmers constantly face (Birhanu and Zeller 2011; Di Falco et al. 2010). Dercon (2009) also showed that about half of all rural households in Ethiopia experienced at least one major drought in the five years preceding 2004, suggesting that climatic shocks are a major cause of transient poverty and welfare loss. For instance, between 1900 and 2009, Ethiopia experienced 12 extreme droughts, which killed over 402,000 people, adversely affected the livelihoods of more than 54 million people, and caused damage of about US $93 million. Similarly, 47 major floods occurred in Ethiopia during the same period, killing 1,957 and affecting 2.2 million Ethiopians, while damaging approximately US$ 16.5 million worth of property (EM-DAT 2009). According to a report of the Ministry of Finance and Economic Development (MoFED 2008), climatic and health shocks remain the most common types of shocks to affect Ethiopian farm households.

Studies on poverty and vulnerability in Africa have also identified Ethiopia as one of the countries most vulnerable to climate change, and one of those with the least adaptive capacity (Orindi et al. 2006; Stige et al. 2006). This is understandable for two reasons. The first is Ethiopia's huge dependence on agriculture. Subsistence agriculture remains the primary source of income for more than 80 percent of Ethiopians and accounts for about 44 percent of the gross domestic product (GDP) of the country. The sector is dominated by smallholder farmers, who produce more than 90 percent of crop output and cultivate more than 95 percent of the crop land (MoFED 2014). Second, the sector depends largely on rainfall, which has become increasingly erratic due to climate change.

In terms of socio-economic conditions, families engaged in subsistence agriculture with higher dependency ratios are found to be highly vulnerable to climatic shocks (World Bank 2005). Changes in the mean rainfall and temperature, as well as the increase in extreme events, affect agriculture, livestock, forestry and fisheries. Small-scale, rain-fed farming and pastoralist systems, inland and coastal fishing and aquaculture communities, and forest-based systems are particularly vulnerable to climate change, with vulnerability varying across communities, dependent on factors including resource ownership, gender, age and health (FAO 2008).

Adaptation, in relation to climate change, is an adjustment in natural or human systems in response to actual or expected shock factors or their effects, in order to moderate harm or exploit beneficial opportunities. Adaptive capacity, on the other hand, is the ability of a system or society to modify its characteristics or behavior so as to cope better with changes brought about by external conditions such as climate change (IPCC 2014). Improving the adaptive capacity of farmers can significantly reduce their vulnerability to climate change (Mendelshon 1998).

Availability and accessibility of a reliable and well-functioning credit market is expected to improve adaptive capacity of farm households. As the life-cycle hypothesis suggests (Friedman 1957), existence of a perfect and complete credit market allows households to borrow the amount of credit they want when they face liquidity problems and repay it in a period of high income. However, in low-income countries, access to credit is limited due to imperfections in the credit market; hence, credit constraints are binding. This may force households to resort to adopting inefficient adaptation strategies that have long-term negative consequences for their future welfare. Crop failure due to rainfall variability, for example, can force farmers to sell their assets to smooth out consumption. In some cases, the value of assets can also drop if shocks persist for a relatively longer period. This implies that climatic shocks, coupled with binding credit constraints, may lead to irreversible loss of productive assets and may put households at risk of future poverty.

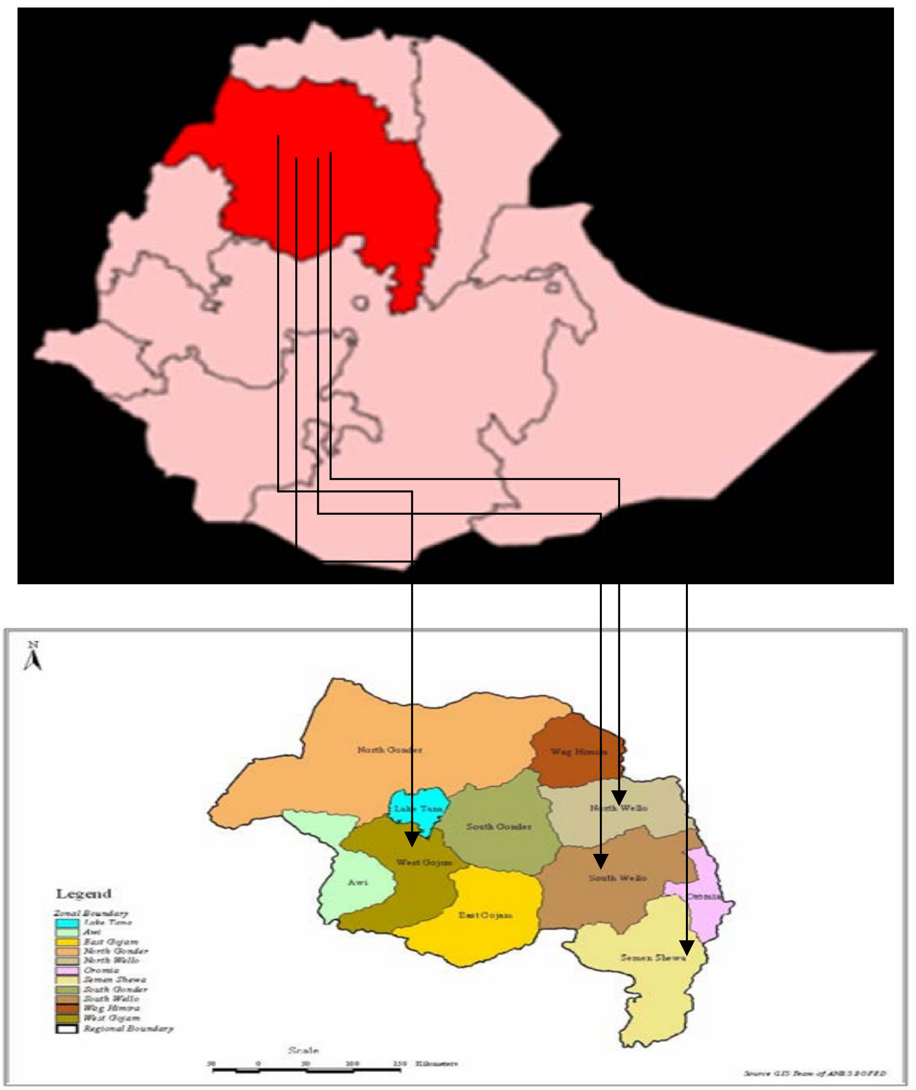
In the context of Ethiopia, there are reasons to expect that the adaptive capacity of farm households is limited due to binding credit constraints (EEA 2011). The lion's share of bank loans in Ethiopia go to finance public enterprises and sectors given priority by the government (IMF 2012: 12). Additionally, Ethiopia ranks 104th out of 185 countries in terms of access to credit (World Bank 2013). Banks in Ethiopia are not willing to lend to smallholder farmers due to the inherent risk of agricultural production and lack of collateral; hence, smallholder farmers are automatically excluded from the formal banking market. Micro-financing institutions and rural credit cooperatives provide alternative formal credit to farm households. However, despite the rapid growth of these institutions in recent years, they reach less than 20 percent of farm households and less than 3 percent of the rural and urban population (AEMFI 2011).

4. The Study Area, Data Set, and Variables

Data used in this study was collected from the Amhara region using two waves of rural household surveys conducted in 2011and 2013.The Amhara National Regional State (ANRS) is situated between 9°–13°45'N latitude and 36°–40°30'E longitude in the north-western part of Ethiopia, with a total land area of 157,126.85 km (which is about 15 percent of the country's land area) and with an altitude ranging from 600 meters above sea level (asl) in the Metema area to 4520 meters asl at Ras Dashen Mountain. The regional economy is highly dependent on agricultural production, which is mainly a smallholder's production system, with the majority practicing traditional methods of farming. Agriculture is the backbone of the regional economy, with a total cultivated area of 4.40 million hectares (33.92 percent of the cultivated area of the country) and total production of 75.68 million quintals (31.89 percent of the country's production). Cereals, pulses, oil seeds, fibers, cotton and root crops are the major crops grown in the region. The region also has a huge potential in terms of livestock population, as it comprises about 25.15 per cent of the Tropical Livestock Units (TLU) of the country (MoFED 2014).

The survey sites include households from four zones (North Shewa, South Wollo, North Wollo and West Gojjam) of the Amhara National Regional State, located in the Northern and Central Highlands of Ethiopia (Figure 1). The surveys were carried out by the Ethiopian Economics Association, in collaboration with the University of California, University of Athens, FAO, and the European Commission Joint Research Center.

Figure 1. Location Map of the Study Area, Ethiopia



Sample households were interviewed on issues related to crop and livestock production, marketing, farm and non-farm income, household consumption expenditure, ownership of assets, participation in non-agricultural enterprises, exposure to drought shocks and credit access. Out of a total of 1200 households, the analysis in this paper is based on balanced panel data for 1,189 households in the years 2011 and 2013. About 33 percent of the sampled households reside in North Shewa zone, 31 percent in West Gojjam, 23 percent in South Wollo, and the remaining 13 percent in North Wollo (Table 1).

Table 1. Sample Households by Zone (2011 and 2013)[5]

Zone	Percent
North Shewa	33.22
West Gojjam	31.12
South Wollo	23.13
North Wollo	12.53
Total	100

Source: Computed from EPIICA's 2011 and 2013 survey data.

4.1. Dependent Variable: Choice of Different Adaptation Strategies

Our analysis considers a number of adaptation strategies, including crop diversification, irrigation, investment in soil conservation and tree planting activities, participation in off-farm employment activities, and drawing down on household productive assets (asset depletion). The soil conservation and tree planting variable is a dummy variable representing the presence of a soil conservation structure or tree(s) on the farmstead. Similarly, participation in off-farm activities is defined as a dummy variable that includes activities such as trading agricultural products, wholesale/retail trade/shop and being employed in non-farm activities for a certain wage. We define farm-level diversification in two ways: count diversity and cash vs. staple crop. Count diversity is defined as the number of crops grown by the household. The second diversification variable is defined as a dummy variable, with one representing a cash crop and zero otherwise. The irrigation and depletion of assets are also dummy variables.

Table 2 presents descriptive statistics of the adaptation strategies in the year 2013. Approximately 53 percent of the sampled households opted for crop diversification,

[5]North Shewa is the reference zone in the empirical analysis.

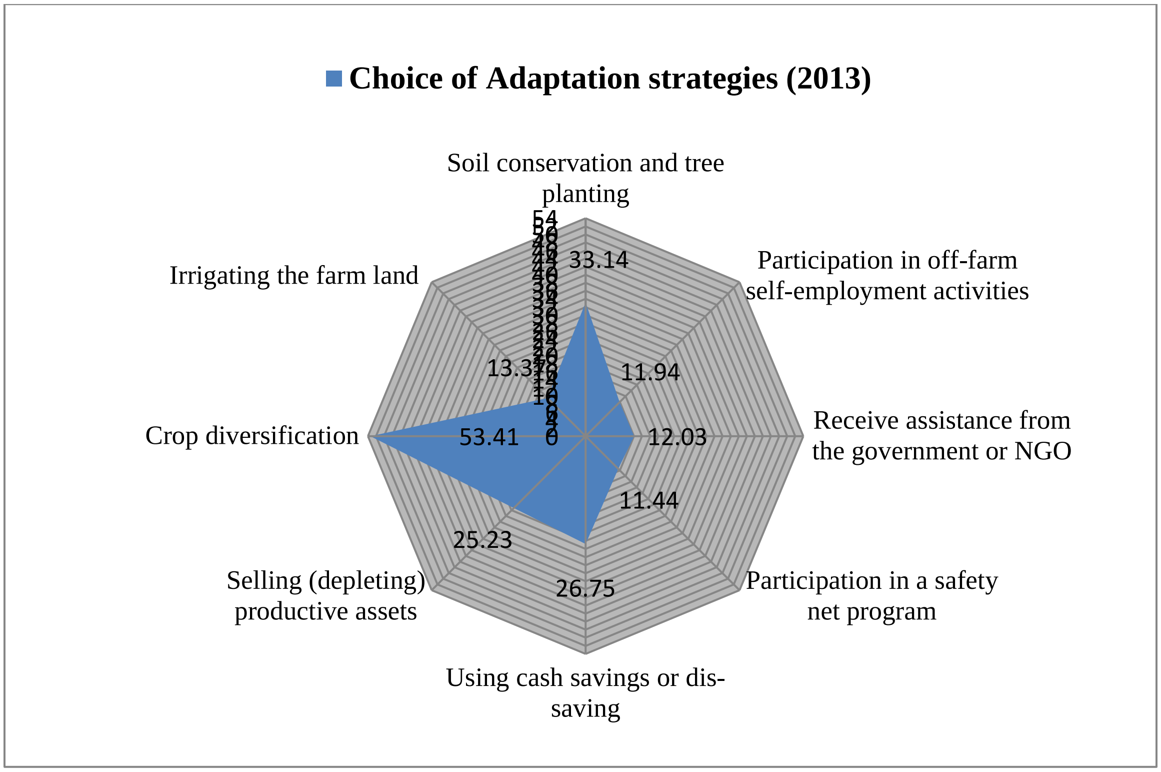
while 33 percent invested in soil conservation activities, including tree planting. Investing in off-farm income generating activities, dis-saving, and depleting productive assets were the other adaptation strategies used by about 12 percent, 27 percent and 25 percent of the sample households, respectively, in 2013 (Figure 2).

Table 2. Choice of Adaptation Strategies by Households in the Sample

Type of Strategy	2011 (percent)	2013 (percent)
Soil conservation and tree planting	24.91	33.14
Irrigating the farm land	5.6	13.37
Crop diversification	26.73	53.41
Selling (depleting) productive assets	41.72	25.23
Using cash savings or dis-saving	26.58	26.75
Participation in a safety net program	13.2	11.44
Receive assistance from the government or NGO	12.28	12.03
Participation in off-farm self-employment activities	10.6	11.94

Source: Computed from EPIICA's survey data.

Figure 2. Household Choice of Adaptation Strategies (2013)



Source: Own figure based on EPIICA's 2011 and 2013 survey.

4.2. Explanatory Variables

We categorized variables explaining farmer's choice of adaptation strategies into measures of climate variability; indicators of credit constraint status; household demographic characteristics; ownership of physical assets; and social capital. Table 3 presents the descriptive statistics of these variables.

4.2.1. Credit Constrained Categories

Identifying constrained households is an empirical challenge because credit rationing cannot be observed directly. However, two identification strategies are documented in the literature (Guirkinger and Boucher 2008; Ayalew and Deininger 2014): the direct and indirect approaches. In this paper, we used the direct elicitation strategy and identified five credit constraint categories. The unconstrained category includes unconstrained borrowers and unconstrained non-borrowers. The unconstrained borrowers are those who have identified themselves as having full access to credit facilities from lending institutions.[6] The unconstrained non-borrowers are those who have stated that they do not borrow from credit institutions because they do not have an urgent need for external finance or they do not have a profitable project that would require a loan. The premise here is that the resource allocation decisions of such households are not affected by the prevailing credit market imperfections.

[6] The credit limit set by lenders to overcome the information asymmetry problem will not be binding for such borrowers.

Table 3. Definition and Summary Statistics of Variables Used in the Data Analysis

Variable	Description	mean	Std. dev.
Dependent variables:	**Choice of 5 different Adaptation strategies**		
Soil_conserv	Soil conservation (1= yes; 0 = otherwise)	0.41	0.49
Crop_divers	crop diversification (1= yes; 0 = otherwise)	0.21	0.41
Off_farm	off-farm employment (1= yes; 0 = otherwise)	0.12	0.32
irrigation	Irrigation (1= yes; 0 = otherwise)	0.13	0.34
Dis_sav	Asset depletion (1= yes; 0 = otherwise	0.3	0.46
Explanatory variables			
Household characteristics			
age	age of the HH head (years)	49.72	14.12
female	1 = household head is female	0.11	0.31
marr	1 = head is married	0.87	0.34
hh_size	household size (number of members of the HH)	5.4	2.05
no_educ	1 = head is uneducated	0.53	0.5
infrml_educ	1 = head attended some informal education	0.26	0.44
frml_educ	1 = head attended some formal education	0.21	0.41
Resource constraints			
lnd_hect	Farm size, ha	0.9	0.7
TLU	Livestock herd size (Tropical Livestock units; TLU)	9.1	9.89
Asset_value	total value of household asset, Birr*	1175.92	2261.27
own_radio	1 = head owns radio	0.25	0.43
Climatic shocks			
rain_cv	Coeff. of variation (CV) of rainfall	0.36	0.11
Mean_rainfall	Annual mean rainfall	104.9	18.3
Mean_temp	Annual mean temperature	32.07	2.8
drought	1 = Household faced drought shock (self-reported)	0.39	0.49
Credit constraint status			
IMR1	Inverse mill's ratio for unconstrained borrowers (from first stage reg)	0.43	0.34
IMR2	Inverse mill's ratio for unconstrained non borrowers (from first stage reg)	0.35	0.28

IMR3	Inverse mill's ratio for quantity constrained borrowers (from first stage reg)	0.45	0.34
IMR4	Inverse mill's ratio for discouraged borrowers (from first stage reg)	0.49	0.37
IMR5	Inverse mill's ratio for risk rationed borrowers (from first stage reg)	0.44	0.34
prvs_cnst	1 = HH faced credit constraint in the previous period (used as IV in the first stage reg.)	0.16	0.37
Social capital (networks)			
Solidarity_group	1 = head is member in a solidarity group (used as IV in the first stage reg.)	0.23	0.42
cp_mem	1 = head is member in a primary farmer's coop.	0.92	0.26
Kebele_asso	1 = head is member of peasant association	0.098	0.28
Ekub_mem	1 = head is member in Ekub (ROSCA)	0.23	0.42
Location dummies			
nshoa	1 = North Shewa zone	0.34	0.47
wgoj	1 = West Gojjam zone	0.31	0.46
swolo	1 = South Wollo zone	0.23	0.42
nwolo	1 = North Wollo zone	0.12	0.33

Source: Own calculation based on EPIICA's survey; *1 Birr = 0.05 USD (on avg.) during the survey period.

Borrowers who have an excess effective demand for credit but face a credit limit due to supply-side limitations were classified as ‘quantity constrained’ households. These households stated that they applied for formal credit and received a loan, but the loan amount was less than their effective demand given the available contract terms. Fourth, from the demand side, there are ‘transaction-cost rationed’ households who have positive effective demand but do not apply for credit. These households reported that they do not want to incur the additional costs associated with the loan application process, including the extra paperwork and the time they waste dealing with lenders. In addition, from their past experience or from their knowledge about lenders’ credit procedures, they are sure that their application will be rejected. Such households may have potentially profitable agricultural projects in mind, but they do not participate in the credit market because their projects become unprofitable once these costs are taken into account. Further, lenders normally want borrowers to bear a certain amount of risk to overcome the moral hazard problem in borrowers’ effort or choice of investment project. One mechanism to do so is to ask for collateral. However, risk-averse households are found to prefer working with their own funds, not putting their land and other assets at risk. These farmers do not want to incur debt even if they qualify for the loan and have a profitable project after accounting for transaction costs.

Table 4 shows categorization of credit constraint status of farm households and their willingness/ability to participate in the formal rural credit market in the study area. The percentage of unconstrained households who did not participate in the credit market has declined from about 43 percent in 2011 to 33 percent in 2013. However, the percentage of households who are quantity constrained has increased from 13 to 23 percent. The percentage of discouraged households has increased from 22 percent in 2011 to 27 percent in 2013. This clearly shows that, although farm households increasingly want to participate in the formal credit market, a growing number of these households are credit constrained.

Table 4. Credit Constraint Status of HHs in the Study Area (Percent)

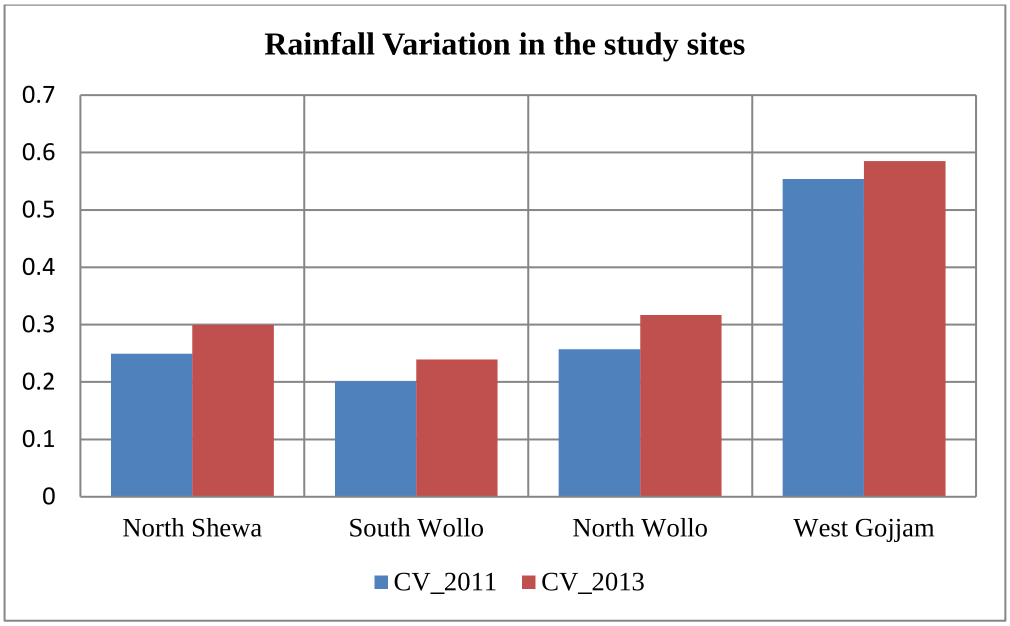
Credit Constraint Category	2011	2013	Full sample
Unconstrained Households			
Borrowers	263(22.1)	205(17.2)	468(19.7)
Non-Borrowers	508(42.7)	389(32.7)	897(37.7)
Total unconstrained households	771(64.8)	594(49.9)	1365(57.4)
Constrained Households			
Quantity Constrained borrowers	152(12.8)	269(22.6)	421(17.7)
Discouraged borrowers	266(22.4)	326(27.4)	592(25.0)
Total constrained households	418(35.2)	595(50.1)	1013(42.7)

Source: Computed from EPIICA's 2011 and 2013 survey data.

4.2.2. A Measure of Climatic Factors

Climatic factors in this paper comprise temperature and rainfall average, rainfall variability and the incidence of drought. Monthly rainfall data were obtained from the National Meteorological Agency of Ethiopia, from eight stations close to the study districts (*woredas*) for the years between 1983 and 2013. The rainfall measure was constructed by taking the sum of monthly rainfall for each year and averaging it over 30 years. The average temperature was also calculated as the monthly temperature average, further averaged over 30 years. Then, we calculated the coefficient of variation (CV) for rainfall, measured as the standard deviation divided by the mean for the respective periods. The major advantage of the CV is that it is scale-invariant and as such provides a comparable measure of variation for households that may have very different wealth levels (Alem and Colmer 2013). As expected, the increasing variability of rainfall over the years in the study area concurs with the national pattern of rainfall variability. Figure 3 shows the coefficient of variation of rainfall across the study zones over time. We linked these climate variables with the household survey data using the thin plate spline regression technique. This method uses latitude, longitude, altitude and other relevant geographic information in linking climate data with survey data (Wahba 1990; Gu 2002; Wood 2003). We also included a dummy variable representing the households' experience of drought shocks.

Figure 3. Rainfall Variation by Year across the Study Zones



Source: Own figure based on EPIICA's 2011 and 2013 survey.

4.2.3. Ownership of Physical Assets and Social Capital

Land holding is an important productive asset that determines the social and economic status of farmers in the study area. The survey data reveals that the mean land holding was about 1.07 hectares (ha) in 2011, which declined to about 0.73 in 2013. A major reason may be the fast population growth in the country in general, and the region in particular. Among the farming communities, farmers in West Gojjam owned relatively larger plots of land in 2011, followed by North Shewa and South Wollo.

The social capital variables included in the analysis are membership in a primary farmer's cooperative association, participation in a *kebele*[7] council, membership in a non-cooperative peasant association and membership in a rotating saving and credit association (ROSCA) as explanatory variables. Membership in these groups is represented by a dummy variable with a value of 1 if respondents belong to these groups and 0 otherwise. These are important social assets enjoyed for their own sake, used for material gain, and called upon in times of shocks or crises (Woolcock and Narayan 2000). On average, 10 percent of the total households interviewed indicated membership in a kebele association, while 23 percent indicated membership in a ROSCA (Table 3).

4.2.4. Socio-Economic Characteristics

Household socio-economic characteristics, such as age, gender, marital status, and level of education of the head, were included in the analysis as control variables. The average age of household heads in the sampled zones is about 50 years, with heads in West Gojjam zone being younger than those in the other three zones. The average household size was approximately five. About nine percent of the households in the study sites were headed by a female in 2011, with this figure having increased to twelve percent in 2013. Compared to the average of 51 percent, the proportion of those without any education in West Gojjam is the highest, at 63% in 2011 and 66% in 2013. On the other hand, 22 percent of the household heads have around 5 years of formal education, whereas 27 percent had attended some informal education as of 2011 and 24 percent as of 2013.

5. Estimation Procedure

The empirical strategy involves estimating the relationships between two key variables: credit constraints and adaptation strategy. However, the nature of the relationship between the two sets of variables as well as the characteristics of each set of variables calls for three major econometric considerations.

First, analysing the impact of credit on different adaptation strategies by simple regression would lead to bias. This is because the decision to participate in the credit market by a household head is likely to be non-random if those who have access to credit have systematically different characteristics from the credit constrained. For example, households with more collateral resources, or those who possess better individual skills,

[7] A *kebele* is the lowest administrative unit in the Ethiopian governance structure.

ability and motivation, may have better access to credit, while those with fewer resources and weak networks are more likely to be credit constrained. Such factors may influence both access to credit and choice of adaptation strategies, resulting in inconsistent estimates of the effect of credit constraints on adaptation activity. In such instances, an appropriate model of analysis requires accounting for possible selection bias.

Second, as discussed in Section 4.1, farmers adopt a mix of technologies to deal with a multitude of agricultural production constraints. This implies that the adoption decision is inherently multivariate, and attempting univariate modeling would exclude useful economic information about interdependent and simultaneous adoption decisions (Dorfman 1996).

Hence, our econometric approach involves a two-stage estimation technique. In the first stage, the determinants of credit constraint are estimated using the generalized linear latent and mixed model (gllamm), whereby the predicted values of different credit constraint categories are obtained. In the second stage, the determinants of adaptation strategy are estimated using a multivariate probit (MVP) model with Inverse Mills Ratios (IMR), included as selectivity correction terms from the first stage.

5.1. Determinants of Credit Constraints: The Generalized Linear Latent and Mixed (gllamm) Model

A unique feature of longitudinal categorical data is the existence of unobserved heterogeneity among the repeated observations for a single individual (Haan and Uhlendorff 2006; Reyes and Lensink 2011). This heterogeneity may occur because each household can make several choices which may not be independent and hence the probabilities of each category for the same household will share the same unobservable random effects. The parameter estimates will be biased if these unobservables are not accounted for. This calls for a more advanced estimation strategy beyond the pooled multinomial model without the random effects. Hence, in the first stage of the analysis, we employed the generalized linear latent and mixed model (gllamm) to fit a multinomial logit model with correlated random intercepts, which accounts for any spurious dependence between different credit constraint categories.

Consider an individual *i* who is faced with *j* different alternatives at time *t*. The probability that this individual falls in a specific category *j* conditional on observed characteristics χ_{it}, which vary between individuals and over time, and also conditional on unobserved individual effects, α_i, which are time constant, can be specified as:

$$prob(j \mid \chi_{it}, \alpha_i) = \frac{\exp(\chi'_{it}\beta_j + \alpha_{ij})}{\sum_{k=1}^{J} \exp(\chi'_{it}\beta_k + \alpha_{ik})} \qquad [5.1]$$

Here, we follow the standard assumption that α is identically and independently distributed over individuals and follows a multivariate normal distribution with mean μ and variance- covariance matrix (Ω), i.e., $\alpha \sim iid(\mu,\Omega)$ (Haan and Uhlendorff 2006; Train 2009).

The likelihood function for Equation (5.1) can be specified as:

$$L = \prod_{i=1}^{N} \int_{-\infty}^{\infty} \prod_{t=1}^{T} \prod_{j=1}^{J} \left(\frac{\exp\left(\chi'_{it}\beta_j + \alpha_j\right)}{\sum_{k=1}^{J} \exp\left(\chi'_{it}\beta_k + \alpha_k\right)} \right)^{d_{ijt}} f(\alpha)\, d\alpha \qquad [5.2]$$

This is so because the choice probabilities given in Equation (5.1) are conditioned on α_i and hence we must integrate over the distribution of α to get the sample likelihood for the multinomial Logit with the random intercepts. This model will be identified if the coefficient vector (β) and the unobserved heterogeneity term (α) of one category are set to zero. Hence, $d_{ijt} = 1$ when individual i falls into category j at time t and zero otherwise.

The problem in solving Equation (5.2) is that we cannot obtain an analytical solution for the integral part of the model. This calls for some form of numerical integration. The literature suggests various simulation and quadrature techniques including the Adaptive Gaussian Quadrature (AGQ), Monte Carlo Simulation, Laplace Approximation, Taylor series approximation, and Gauss Hermite quadrature to solve this problem (Hartzel et al. 2001; Rabe-Hesketh et al. 2004). Among these simulation and quadrature techniques, the AGQ approach is preferred for longitudinal categorical data because it is computationally more efficient than the ordinary quadrature in performing the numerical integration of Equation (5.2). Another advantage of using the AGQ is that the number of quadrature points required to approximate the integral are much lower than that of the ordinary quadrature and prior studies have used this technique to evaluate similar integrals (examples include Hartzel et al. (2001); Rabe-Hesketh et al. (2004); and Haynes et al. (2006)).

STATA software has a procedure called the generalized linear, latent and mixed model (gllamm), which is designed to model categorical dependent variables with repeated observations (Rabe-Hesketh et al. 2004; Haan and Uhlendorff 2006). It is an extension of the generalized linear model because it incorporates both the fixed and random effects and hence the response distribution is defined conditionally on the random effects. This model takes care of individual unobservable heterogeneity by accounting for the possible correlation of choices made by individuals.

As the gllamm estimation is supposed to serve the purpose of correcting for selection bias, we include two variables as instruments. The first is the lag of credit access – a dummy variable capturing past information regarding whether the household has accessed any credit during the past year. The second is membership in a social group, again a dummy variable representing whether the household belongs in a social network. After regressing this model (Equation 5.2), we impute the Mills ratios and thereafter we include the Mills ratios as a regressor in our outcome model to correct for the selection bias. This approach has been employed by, among others, Millet (2001); Okten et al. (2004) and Bushway et al. (2007). The intuition behind this approach is that by including the Inverse Mills Ratio from the first stage model as a regressor in the second stage multivariate probit model, we obtain estimators that are free from the biasn caused by sample selection (Wooldridge 2002; Gujarati 2004; and Greene 2004).

5.2. Choice of Adaptation Strategies: Multivariate Probit Model

Our analytical approach for the second stage extends the model by Rahm and Huffman (1984) and Adesina and Zinnah (1993) that links farmers' utility to the choice of a given agricultural technology (in our case, adaptation strategy) by adding credit constraints and environmental risk representing climate change. Accordingly, the adaptation equation is represented by:

$$P_{it} = \beta X_{it} + c_i + \epsilon_{it} \qquad [5.3]$$

For farmer *i*, at time *t*, P is a dummy variable with $P = 1$ if the adaptation strategy is adopted and $P = 0$ otherwise. β is a vector of parameters to be estimated; X_{it} is a vector of explanatory variables representing socio-economic, credit and climatic factors; c_i is the unobserved individual effect, which is assumed to be independent of $X_{it}X$; and ϵ_{it} is a random error term,

$$\epsilon_{it} \sim I.I.D.N(0, \sigma_\alpha^2), \text{ and } c_i | X_i \sim N(0, \sigma_\alpha^2),$$

The likelihood function of the random effects (RE) probit model relies on the probabilities:

$$Pr(y_{it} = 1|x_{it}, c_i) = \Phi(x_{it}\beta + c_i) \quad [5.4]$$

where $\Phi(.)$ is either the standard normal CDF (probit) or the logistic CDF (logit).

The random effects model is associated with the strong assumption of no correlation between the unobserved individual effect c_i and the regressors/observed covariates (Baltagi 2005). However, this is unlikely, because some of the time-invariant characteristics, such as farmer's motivation or ability, may be correlated with some of the regressors in the model. The fixed effects estimator, on the other hand, relies on a transformation to remove this individual-specific constant term, along with time-invariant observed covariates (Wooldrige 2003).

Therefore, it is necessary to adopt a method that allows for correlation between c_i and x_{it}. Our estimation procedure involves the pseudo-fixed effects estimation (Mundlak's) approach (Wooldridge 2003), which involves explicitly modeling the relationship between time-varying regressors and the unobservable effect in an auxiliary regression (Mundlak 1978). In particular, c_i can be approximated by a linear function:

$$c_i = \omega\bar{s}_{im} + \zeta_{im} \quad [5.5]$$

where $\bar{s}_{im}$ represents a vector of time-variant explanatory variables and ω is a vector of parameters to be estimated. Averaging over *t* for a given *i* and substituting the resulting expression into (5.4) gives:

$$P_{it}^* = x_{it}\beta + \omega\bar{s}_{it} + \xi_{it} \quad [5.6]$$

where P_{it}^* is the choice of a given adaptation strategy by household *i* in year t. Moreover, if we assume the error terms are independently and identically distributed across adaptation strategies, we estimate five separate adoption models for five different adaptation strategies. This assumes no interdependence among the strategies. However, a farmer may adopt two or more strategies simultaneously or the adoption of one strategy may be conditioned on the adoption of another strategy, because they are either substitutes or complements.

Thus, a single equation estimation approach could cause bias and inefficiency in the parameters if the interdependence is observed and/or if unobserved heterogeneity is correlated among these strategies (Greene 2008). Following Teklewold et al. (2013) and

Kassie et al. (2013), we used a Multivariate Probit method (MVP[8]), which is a non-linear seemingly unrelated simultaneous equation model, and also a linear seemingly unrelated simultaneous equation model (SURE[9]), which allows correlation among the unobserved disturbances. This approach is found to be better suited to the adoption decisions for interrelated adaptation strategies. We also tested interdependence of technologies in the adoption decisions by checking the sign and significance of the off-diagonal elements of the variance-covariance matrix of the Multivariate Probit Model (MVP) and the SURE model. A positive sign is interpreted as a complementary relationship among the adaptation strategies, while a negative correlation is interpreted as substitutes.

6. Discussion of Results

As discussed in Section 3, the adaptation strategies considered in the empirical analysis include soil conservation, participation in off-farm self-employment, crop diversification, irrigation, and depletion of household assets. Below, we discuss the quantitative relationship between these adaptation strategies and credit constraints, with climate-related variables as key conditioning factors. Before that, we present the determinants of credit constraint status, which is an endogenous determinant in the adaptation equations.

6.1. Determinants of Credit Constraint Status

Table 5 reports the determinants of the credit constraint category of households. The five important credit constraint categories that were considered in the analysis include unconstrained borrowers, unconstrained non-borrowers, and quantity constrained, discouraged, and risk rationed borrowers. The first category is used as a base case. Overall, factors such as age, gender, land holding, and experience of shock turned out to be the most important determinants of credit constraint in all the cases considered, amid variations in the sign, level of significance and magnitude of the coefficients. Variables explaining the credit constraint status of farm households are categorized into: (i) household demographic characteristics; (ii) ownership of livelihood assets; (iii) risk preference behavior; (iv) institutional constraints; and (v) location and exposure to climatic shocks.

The results show that households living in South Wollo zone tend to be highly discouraged and quantity constrained, relative to households residing in the other three

[8] We would like to thank the referees for suggesting the MVP method, which greatly improved our estimation.

[9] We used the SURE model as a robustness test for the second definition of the crop diversification count variable since MVP works only for binary dependent variables.

zones of the study area. According to the World Bank (2005), 45 percent of the South Wollo zone is exposed to drought and malaria. This seems logical, in that access to external sources of finance is very difficult in such a fragile environment, because lenders are not willing to take uninsured risks of default in the case of crop failure due to climatic shocks. Households residing in West Gojjam zone, however, are found to have relatively better access to formal credit. This may be because West Gojjam is a relatively more fertile region of the country.

Table (5) also presents institutional constraints in the credit market of the study area, including high transaction costs of borrowing associated with the loan application process, paperwork, and distance, as well as institutional mistakes made in selecting applicants. As expected, the results also depict a significant positive effect of these constraints on the probability of being credit constrained. Such high transaction costs of borrowing discourage genuine applicants who want to have access to rural finance.

We used the year dummy as a control variable to capture the change in credit constraints and borrowing behavior of farm households between 2011 and 2013. The result shows that the probability of being quantity constrained increased by about 61 percent, which implies that farm households do not get the amount of credit for which they apply.

Among the socio-economic variables, age of the household head is found to have a positive and statistically significant effect on the probability of being discouraged. The result shows that gender has a negative and significant effect on the probability of being credit constrained. This implies that female-headed households have higher probability of access to rural credit, compared to their male counterparts in the context of the study area. This may be due to the recent micro-credit revolution, which focuses more on empowering women. It agrees with the actual case in rural Ethiopia, where 54 percent of the clients of micro-finance institutions are female (EEA 2011). Ashraf et al. (2003) showed that credit schemes which favor female-headed households have gained popularity in recent years and have become successful. Aterido et al. (2011) reached a similar conclusion.

Table 5. Determinants of Credit Constraint Categories—Result from gllamm

Variable	Unconstrained non-borrowers	Constrained - Quantity rationed borrowers	Discouraged - Tran. cost constrained borrowers	Discouraged - risk-rationed borrowers
Age	.0231***	0.0127*	0.0276***	0.016**
	(0.007)	(0.007)	(0.007)	(0.008)
Female	-1.4***	-0.553	-1.08**	-1.439***
	(0.454)	(0.44)	(0.461)	(0.535)
Married	-.745*	-0.424	-0.735*	-1.066**
	(0.422)	(0.423)	(0.431)	(0.485)
Household size	-0.077	-0.0245	0.055	0.01
	(0.05)	(0.048)	(0.051)	(0.049)
No educ.	.459**	-0.2	.497**	0.413
	(0.228)	(0.213)	(0.237)	(0.283)
Formal educ.	-0.106	0.107	0.178	0.354
	(0.239)	(0.223)	(0.247)	(0.299)
Land hect.	.466***	0.001	0.134	0.216

	(0.12)	(0.123)	(0.125)	(0.171)
Tropical Livestock Units (TLU)	-1.28**	-0.795	-1.11*	-0.471
	(0.568)	(0.574)	(0.579)	(0.676)
Coop member	0.0732	0.137	-0.11	-0.543
	(0.302)	(0.308)	(0.307)	(0.338)
Year dummy	-0.148	.613***	0.159	0.188
	(0.183)	(0.189)	(0.19)	(0.327)
Ln(food exp)	0.191	0.035	.274**	0.236*
	(0.121)	(0.119)	(0.126)	(0.142)
Drought shock	0.18	.459**	0.279	0.206
	(0.187)	(0.181)	(0.192)	(0.285)
West Gojjam	-1.65***	-0.136	-1.32***	-0.726***
	(0.228)	(0.209)	(0.229)	(0.269)
South Wollo	1.56***	1.63***	1.38***	1.085***
	(0.279)	(0.288)	(0.284)	(0.312)
North Wollo	-.493*	.93***	-.909***	-1.291***

	(0.297)	(0.271)	(0.314)	(0.406)
HH faced credit constraint last year	-0.989***	-0.352	0.158	1.688***
	(0.244)	(0.284)	(0.494)	(0.412)
head is member in a solidarity group	-2.684***	-1.365***	-1.880***	-2.957***
	(0.212)	(0.214)	(0.431)	(0.278)
Constant	0.944	-0.22	-0.283	-1.269
	(0.95)	(0.947)	(0.982)	(1.167)
Statistics				
Log likelihood	-2794.11			
Obs.	2294			

Note: * p < .1; ** p < 0.05; *** p < 0.01; robust standard errors in bracket. UCNB, QCB, and DISC stand for unconstrained non-borrower, quantity constrained borrower, and discouraged borrower.

As discussed in Section 5.1, we included two variables as instruments: (1) the lag of credit access, a dummy variable capturing past information regarding whether the household has accessed any credit during the past year; and (2) membership in a solidarity group, again a dummy variable representing whether the household belongs to a social network. The result shows that having faced credit constraint in the previous period significantly discourages participation in the credit market. Household heads who are members of a social group, however, are found to be less constrained and more likely to participate in the rural credit market. We tested the joint significance of these variables and imputed the Mills ratios to be included as regressors in our outcome model to correct for the selection bias. This is also a common approach in the literature; see, for example, Okten et al. (2004), Bushway et al. (2007) and Teklewold et al. (2013).

6.2. Credit Constraints and Participation in Off-Farm Income Generating Activities

Table 6 presents determinants of the probability of participating in off-farm income generating activities for different credit constraint categories. The coefficients show negative impacts on off-farm employment as a result of being in the discouraged and risk rationed borrower categories. These results demonstrate that credit constraints adversely affect the probability of participation in off-farm employment. These results are also in line with our review of the literature in Section 2, which indicated that at least some of the activities require start-up capital and institutional support. This finding is in line with empirical studies in Honduras (Ruben and van den Berg 2001) Columbia (Deininger and Olinto 2001) and Peru (Escobals 2001).

The coefficient of variation (CV) of rainfall is found to have no significant effect on the choice to participate in off-farm income generating activities.[10] Similarly, the incidence of drought shock is not a significant determinant of participation in off-farm employment activities.

The interaction between credit constraint and coefficient of variation of rainfall is significant for the risk rationed group. This suggests that, when coupled with credit constraints, the adverse effects of climate variability are intensified. Further, the

[10] As a robustness check, we used mean rainfall and mean temperature in place of coefficient of variation of rainfall. Mean rainfall is a signficant and positive determinant of adaptation in all the categories, while the effect of temperature is not significant; see Table (5A-9A) .

incidence of drought was interacted with the credit constraint variable; however, the coefficients are not significant.

Table 6. Effect of Credit Constraints and Climatic Factors on Off-Farm Self-Employment: A Multivariate Probit Model with Rainfall CV, Mean Temperature, and Mundlak Effects

Dependent variable: Participation in Off_farm employment (IGA)		
VARIABLES	coefficient	std.err.
Credit constraint categories		
Unconst.non Borrower (IMR)	0.105	0.149
Quantity constrained Borrower (IMR)	0.236*	0.175
Discouraged Borrower (IMR)	0.040	0.214
Risk rationed Borrower (IMR)	-0.128	0.145
Climate variables		
Rainfall CV	-0.098	0.235
Mean Temperature	-0.015	0.174
Mean Temperature sqr	0.001	0.003
Household faced drought shock (self-reported)	0.155	0.134
Interaction terms		
Qnty_const * rain_CV	-0.765**	0.341
risk_rashned * rain_CV	-0.629**	0.319
Discouraged * rain_CV	-0.385	0.605
Physical asset and plot characteristics		
Land owned (hectare)	-0.243*	0.158
Tropical Livestock Units (TLU)	0.033	0.173
Own radio (proxy for info.)	0.128	0.199
Household Characteristics		
Age of head	-0.011***	0.004
dummy for female head of the household	0.363*	0.280
Dummy for a married head	-0.086	0.260
Household size	-0.136	0.144
Head has no education	-0.175	0.243
Head attended some formal education	-0.318	0.322
Time Average (Mundlak)		
Land owned (time_avg)	0.110	0.192
Head has no education (time_avg)	0.234	0.304

Head attended some formal educ. (time_avg)	0.774**	0.370
Own radio (proxy for info.) (time_avg)	0.021	0.263
Tropical Livestock Units (TLU) (time_avg)	-0.032	0.174
Household size (time_avg)	0.184	0.145
year dummy	0.089	0.252
Location factors		
Dummy for West Gojjam	-0.337*	0.214
Dummy for South Wollo	-0.207	0.218
Dummy for North Wollo	-0.315	0.255
Constant	-0.437	2.208
Statistics		
Observations	1140	
Wald chi-square	525.48	
Prob > chi2 =	0	
Log likelihood =	-2632.239	

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

Our results also hold when other controls, such as physical and social capital variables, household socio-economic characteristics and location dummies are included in the model.

The results show that female heads are more likely to participate in off-farm employment. This may be because females have better access to credit in the context of the study area, as discussed in Section 6.1. Having some formal education also appears to have a positive impact on off-farm employment participation, as evidenced by its significant coefficient.

6.3. Credit Constraints and Crop Diversification

Table 7 presents the effect of credit constraints and climatic factors on crop diversification. We captured the level of diversification using a dummy variable coded as one for households who plant a greater number of crops on their plots (for example, cash crops such as vegetables, pulses, oil seeds, etc.) and zero for those who plant a smaller number of crops (for example, traditional staples such as cereals only). From the results, we note that quantity constrained households tend to diversify more, while discouraged borrowers diversify significantly less. This could be explained by the fact that planting cash crops is risky and requires substantial cash outlays to purchase inputs such as seeds and fertilizers. Prior studies also confirm that access to credit is one of the critical factors in the crop diversification decisions of farm households (see Section 2).

Table 7. Effect of Credit Constraints and Climatic Factors on Crop Diversification Decision: A Multivariate Probit Model with Rainfall CV, Mean Temperature, and Mundlak Effects

Dependent variable: crop diversification		
VARIABLES	coefficient	std.err.
Credit constraint categories		
Unconst.non Borrower (IMR)	-0.782	0.567
Quantity constrained Borrower (IMR)	3.211	2.410
Discouraged Borrower (IMR)	-7.434**	2.956
Risk rationed Borrower (IMR)	0.373	0.792
Climate variables		
Rainfall CV	0.732***	0.255
Mean Temperature	0.320**	0.146
Mean Temperature sqr	-0.006**	0.003
Household faced drought shock (self-reported)	-0.340**	0.160
Interaction terms		
Qnty_const * rain_CV	0.323	0.308
risk_rashned * rain_CV	-0.053	0.180
Discouraged * rain_CV	-0.125	0.121
Physical asset and plot characteristics		
plot has flat slope (base cat. = steepy slope)	0.263	0.232
plot has gentle slope	0.317	0.243
distance_to_plot	0.001	0.002
Land owned (hectare)	-0.115	0.142
Tropical Livestock Units (TLU)	0.178	0.147
Own radio (proxy for info.)	0.008	0.175
Household Characteristics		
Age of head	0.011**	0.005
dummy for female head of the household	0.659**	0.281
Dummy for a married head	-0.149	0.230
Household size	0.029	0.119
Head has no education	-0.417**	0.218
Head attended some formal education	0.083	0.283

Time Average (Mundlak)		
Land owned (time_avg)	-0.353**	0.175
Head has no education (time_avg)	0.423**	0.250
Head attended some formal educ. (time_avg)	0.066	0.325
Own radio (proxy for info.) (time_avg)	-0.109	0.230
Tropical Livestock Units (TLU) (time_avg)	-0.181	0.148
Household size (time_avg)	-0.020	0.122
year dummy	0.515**	0.221
Location factors		
Dummy for West Gojjam	-1.001***	0.194
Dummy for South Wollo	0.113	0.310
Dummy for North Wollo	0.034	0.296
Constant	-2.175	3.495
Statistics		
Observations	1140	
Wald chi-square	525.48	
Prob > chi2 =	0	
Log likelihood =	-2632.239	

*** p < 0.01, ** p < 0.05, * p < 0.1

The impact of climatic factors, measured by the coefficient of variation of rainfall, shows that the coefficient of variation of rainfall is not a significant determinant of crop diversification. In order to assess the impact of credit constraints conditional on rainfall variability, we interact these two sets of variables. We find that the interaction between rainfall variability and credit constraint has no significant impact on diversification. Similarly, the results from the interaction between credit constraint dummies and the incidence of drought show no significant impact. This could be because climatic variability is not sufficient for the effect to manifest in the diversification decision. The benefit of diversification, in terms of acting as a shock-absorber against environmental variability, is conditional on the severity of the variability; in other words, the level of environmental variability needs to be sufficiently high (Bezabih and Gaeback 2010; Di Falco et al. 2010) or risk-prone areas with high rainfall variability need to be targeted (Di Falco and Chavas 2009).

Of the socio-economic characteristics, farmers who have no education and have larger land holdings tend to diversify less. Other variables, such as household size, marital status, and plot characteristics, are found to have no significant impact on the decision to diversify.

As a robustness check, we also defined crop diversification as count diversity. The count diversity is constructed as the number of crops grown on a farm in any given year (see Benin et al. 2014). So, if we have teff, maize, wheat, and barley grown in year 2011 in household 1, then the count diversity of household 1 will be 4. For this definition, we used the seemingly unrelated regression (XTSUR) model to estimate the effect of credit constraints and climatic factors on crop diversification. The result is given in Table 7A in the appendix. From the results, we note that facing drought shock forces farmers to plant a greater number of crops as a risk diversification strategy, while risk rationing in the credit market compels them to plant a significantly lower number of crops. This agrees with our result in Table 7.

6.4. Credit Constraints, Tree Planting and Soil Conservation

As per the results in Table 8, we found that credit constraints have no significant effect on land conservation activities. Similarly, neither the coefficient of variation of rainfall nor the incidence of drought are significant determinants of soil conservation and tree planting activities. The interaction between the coefficient of variation of rainfall and credit constraints is also not significant, indicating that soil conservation practices may not be responsive to credit availability/constraints. One plausible explanation for this insignificant coefficient is that soil conservation and afforestation measures are highly subsidized by the government. Mekonnen and Damte (2011) found similar results, where credit constraints had no significant effect on the likelihood of investing in soil conservation and tree planting in Ethiopia.

The exception, the reduction in the propensity to invest in soil conservation for the discouraged category of borrowers, is negative and significant when interacted with drought shock. This indicates some evidence of the potency of credit constraints in hampering conservation activities in the incidence of drought shock. This is in line with findings by Di Falco and Veronsi (2014) and Teklewold et al. (2015), who find a significant role of soil conservation in acting as an adaptation mechanism.

Older heads of household, household size, and education are positively and significantly associated with soil conservation activities.

Table 8. Effect of Credit Constraints and Climatic Factors on Soil Conservation and Planting Trees: A Multivariate Probit Model with Rainfall CV, Mean Temperature, and Mundlak Effects

Dependent variable: Soil Conservation and Planting Trees		
VARIABLES	coefficient	std.err.
Credit constraint categories		
Unconst.non Borrower (IMR)	-0.392	0.472
Quantity constrained Borrower (IMR)	-0.826	2.000
Discouraged Borrower (IMR)	-6.102**	2.737
Risk rationed Borrower (IMR)	-0.379	0.691
Climate variables		
Rainfall CV	0.144	0.187
Mean Temperature	0.252**	0.131
Mean Temperature sqr	-0.006**	0.003
Household faced drought shock (self-reported)	-0.061	0.140
Interaction terms		
Qnty_const * rain_CV	-0.255	0.280
risk_rashned * rain_CV	-0.072	0.157
Discouraged * rain_CV	-0.040	0.129
Physical asset and plot characteristics		
plot has flat slope (base cat. = steepy slope)	0.323*	0.190
plot has gentle slope	0.493***	0.202
distance_to_plot	0.003**	0.002
Land owned (hectare)	0.105	0.116
Tropical Livestock Units (TLU)	-0.061	0.130
Own radio (proxy for info.)	0.139	0.154
Household Characteristics		
Age of head	0.007*	0.004
dummy for female head of the household	0.152	0.249
Dummy for a married head	-0.087	0.206
Household size	0.293***	0.106
Head has no education	-0.109	0.188
Head attended some formal education	0.309	0.251
Time Average (Mundlak)		
Land owned (time_avg)	-0.002	0.141
Head has no education (time_avg)	0.346*	0.216

Head attended some formal educ. (time_avg)	-0.164	0.286
Own radio (proxy for info.) (time_avg)	-0.403**	0.203
Tropical Livestock Units (TLU) (time_avg)	0.057	0.130
Household size (time_avg)	-0.247**	0.108
year dummy	0.383**	0.203
Location factors		
Dummy for West Gojjam	0.223*	0.168
Dummy for South Wollo	-0.793***	0.183
Dummy for North Wollo	-0.150	0.254
Constant	1.830	2.990
Statistics		
Observations	1140	
Wald chi-square	525.48	
Prob > chi2 =	0	
Log likelihood =	-2632.239	

*** p < 0.01, ** p < 0.05, * p < 0.1

6.5. Credit Constraints and Household Assets Depletion

The results in Table 9 show that being in the risk rationed borrower's category significantly increases the likelihood of asset depletion. This probability significantly increases when rainfall variability is interacted with risk rationing. This implies that adverse effects of climate variability are more severe for risk rationed households, who are shown to resort to asset depletion. However, the interaction between the credit constraint variable and drought gives insignificant results. The result further shows that farmers who are members of a ROSCA are less likely to engage in asset depletion, while other social capital variables are found to have no effect on the asset depletion decision.

Table 9. Effect of Credit Constraints and Climatic Factors on Depleting Productive Assets: A Multivariate Probit Model with Rainfall CV, Mean Temperature and Mundlak Effects

Dependent variable: Depleting Productive Assets		
VARIABLES	Coefficient	std.err.
Credit constraint categories		
Unconst.non Borrower (IMR)	1.742***	0.497
Quantity constrained Borrower (IMR)	2.211	1.864
Discouraged Borrower (IMR)	1.979	2.403
Risk rationed Borrower (IMR)	0.904	0.714
Climate variables		
Rainfall CV	0.629***	0.191
Mean Temperature	-0.164	0.139
Mean Temperature sqr	0.004*	0.003
Household faced drought shock (self-reported)	-0.081	0.112
Interaction terms		
Qnty_const * rain_CV	0.580**	0.278
risk_rashned * rain_CV	0.532***	0.161
Discouraged * rain_CV	0.859**	0.474
Physical asset and plot characteristics		
plot has flat slope (base cat. = steepy slope)	0.048	0.185
plot has gentle slope	-0.218	0.199
distance_to_plot	-0.003*	0.002
Land owned (hectare)	0.235**	0.116
Tropical Livestock Units (TLU)	0.260**	0.134
Own radio (proxy for info.)	0.094	0.158
Household Characteristics		
Age of head	0.002	0.004
dummy for female head of the household	0.106	0.260
Dummy for a married head	0.316	0.217
Household size	-0.139	0.107
Head has no education	0.188	0.190
Head attended some formal education	0.344	0.257
Time Average (Mundlak)		
Land owned (time_avg)	0.080	0.143
Head has no education (time_avg)	-0.247	0.221

Head attended some formal educ. (time_avg)	-0.171	0.291
Own radio (proxy for info.) (time_avg)	-0.214	0.207
Tropical Livestock Units (TLU) (time_avg)	-0.266**	0.134
Household size (time_avg)	0.174*	0.109
year dummy	-0.186	0.220
Location factors		
Dummy for West Gojjam	-0.309*	0.175
Dummy for South Wollo	-0.287	0.187
Dummy for North Wollo	0.390*	0.250
Constant	-4.593*	2.758
Statistics		
Observations	1140	
Wald chi-square	525.48	
Prob > chi2 =	0	
Log likelihood =	-2632.239	

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

6.6. Credit Constraints and Investment in Small-Scale Irrigation

The results in Table 10 indicate that facing drought shock is the main driver of investment in small-scale irrigation in the study sites. This behavior has been increasing over the years spanning our analysis, as the positive and significant year dummy confirms. One reason for this improvement may be the priority given by the government to small-scale irrigation projects in recent years, in order to increase agricultural productivity and tackle the adverse effects of climate change to promote green growth (MoFED 2014). The socio-economic control variables, except for age, are found to be non-significant.

Table 10. Effect of Credit Constraints and Climatic Factors on Investing in Small-scale Irrigation: A Multivariate Probit Model with Rainfall CV, Mean Temperature, and Mundlak Effects

Dependent variable: Investing in Small-scale Irrigation		
VARIABLES	coefficient	std.err.
Credit constraint categories		
Unconst.non Borrower (IMR)	0.269*	0.157
Quantity constrained Borrower (IMR)	0.412	0.512
Discouraged Borrower (IMR)	0.696***	0.240
Risk rationed Borrower (IMR)	0.074	0.159
Climate variables		
Rainfall CV	0.430	0.296
Mean Temperature	0.110	0.155
Mean Temperature sqr	-0.002	0.003
Household faced drought shock (self-reported)	-0.300	0.246
Interaction terms		
Qnty_const * rain_CV	-0.118	1.129
risk_rashned * rain_CV	0.025	0.292
Discouraged * rain_CV	-4.311	116.998
Physical asset and plot characteristics		
plot has flat slope (base cat. = steepy slope)	0.630**	0.285
plot has gentle slope	0.332	0.299
distance_to_plot	-0.001	0.002
Land owned (hectare)	-0.096	0.133
Tropical Livestock Units (TLU)	-0.356**	0.166
Own radio (proxy for info.)	-0.103	0.188
Household Characteristics		
Age of head	-0.006*	0.004
dummy for female head of the household	-0.301	0.267
Dummy for a married head	-0.289	0.235
Household size	0.127	0.112
Head has no education	0.095	0.218
Head attended some formal education	0.532*	0.315
Time Average (Mundlak)		
Land owned (time_avg)	0.142	0.171
Head has no education (time_avg)	0.171	0.267

Head attended some formal educ. (time_avg)	-0.365	0.357
Own radio (proxy for info.) (time_avg)	0.255	0.244
Tropical Livestock Units (TLU) (time_avg)	0.352**	0.167
Household size (time_avg)	-0.146	0.115
year dummy	-0.003	0.218
Location factors		
Dummy for West Gojjam	-0.839***	0.241
Dummy for South Wollo	0.922***	0.256
Dummy for North Wollo	0.867***	0.277
Constant	-3.260	2.176
Statistics		
Observations	1140	
Wald chi-square	525.48	
Prob > chi2 =	0	
Log likelihood =	-2632.239	

*** p < 0.01, ** p < 0.05, * p < 0.1

Table 11. Estimated Covariance Matrix of the Multivariate Probit Model (MVP) Regression between Different Adaptation Strategies

	ρ_C	ρ_E	ρ_T	ρ_D	ρ_I
ρ_C	1				
ρ_E	0.34 (0.068)***	1			
ρ_T	0.27 (0.053)***	0.099(0.066)*	1		
ρ_D	-0.066 (0.059)	-0.18(0.069)***	0.028(0.052)	1	
ρ_I	0.035 (0.068)	-0.002(0.080)	0.047(0.065)	0.015(0.065)	1

Likelihood ratio test of: rho21 = rho31 = rho41 = rho51 = rho32 = rho42 = rho52 = rho43 = rho53 = rho54 = 0

$\chi^2(10) = 58.95$

Prob> $\chi^2 = 0.00$

7. Conclusions

This study empirically investigated the links between alternative adaptation strategies and different forms of credit constraints in selected areas of the Amhara Regional State of Ethiopia using household-level panel data. Key determinants of the choice of adaptation strategies include constraint status (being a risk rationed, discouraged, or unconstrained borrower); exposure to climatic factors; household demographic characteristics; ownership of livelihood assets; and other control variables such as location. The quantitative analysis points to the fact that the type of credit constraint matters for the choice of adaptation strategies of households.

The findings of the study can be summarized in four major ways. First, the existence of a significant proportion of discouraged and risk rationed borrowers indicates that the rural credit market in Ethiopia is not yet inclusive; we found that this reduces the adaptive capacity of farm households. For instance, discouraging credit policies and procedures reduces the probability of participation in off-farm employment. This can be explained by the fact that lenders usually make their credit procedures very stringent to solve the screening, monitoring, and moral hazard problems that are very common in the credit market of developing countries (Stiglitz and Weiss 1981; Antwi and Antwi 2010). Further, the adaptive capacity of risk rationed farmers has significantly decreased. This can be explained by the fact that lenders require borrowers to bear some amount of risk in the form of collateral. Second, relatively better credit access seems to have encouraged irrigation, while credit constraint seems to have discouraged participation in off-farm employment and diversification. This largely significant impact of the different credit constraint categories on participation in alternative adaptation strategies confirms the critical role credit availability has in adaptation investment. Similarly, the importance of the interaction terms between rainfall variability and credit constraint categories in the choice of adaptation strategies indicates the importance of credit, especially with greater effect of climatic factors. As shown in Table 11, there is a strong interdependence in the choice of adaptation strategies by a given household.

The role of credit in the uptake of the different adaptation strategies underlines the need to understand the links between credit institutions and the other institutions directly linked with the different adaptation strategies, such as seed delivery mechanisms (in relation to diversification), land tenure arrangements (in relation to tree planting and soil conservation), and general agricultural extension systems (in relation to irrigation activities). Further, given the links between credit constraints and climatic factors noted in this study, increasing awareness about how the credit market works and provision of climate information can help farmers better adapt to climate change. Administrative zones such as South and North Wollo, which are more vulnerable to climate variability, need special assistance so that they may have better access to the rural credit market and build their adaptive capacity.

Responsiveness of adaptation strategies may differ depending on whether credit is accessed from the informal or formal sector. It should be noted that the analysis does not go into the potentially differing impacts of formal and informal credit access and their possible interactions. Given the lack of detailed information on the nature of credit access from the informal sector, as opposed to the kind of information we were able to extract on formal sector credit access, it was not possible to look in depth into credit access by degree of formality. For the future, a more detailed analysis of credit access by the nature of formality is required.

While the paper makes an important stride in jointly analysing the role of credit constraints in different climate adaptation strategies, there are two key shortcomings of the paper. First, our analysis of the responsiveness of adaptation strategies to climatic factors uses measures such as the 30 year mean of temperature and rainfall as well as the 30 year coefficient of variation of rainfall. This does not encompass the climate change responses of these adaptation strategies, as the analysis does not incorporate actual climate change measures. Furthermore, the analysis does not assess the welfare impacts of the adaptation strategies, focusing only on the responsiveness of the strategies to credit constraints. Both these gaps are subjects worthy of further investigation.

The policy implications of this paper also go beyond the role of credit in adaptation to climate change. Policies that enhance and strengthen institutional support may also be valuable in enhancing the adaptation capacity of households. Hence, in future research, it is worth investigating the role of similar institutions in the context of climate change adaptation.

References

Adesina, A., and M. Zinnah. 1993. Technology Characteristics, Farmers' Perceptions and Adoption Decisions: A Tobit Model Application in Sierra Leon. *Agricultural Economics* 9: 297-311.

Adger, W.N., S. Huq, K. Brown, D. Conway, and M. Hulme. 2003. Adaptation to Climate Change in the Developing World. *Progress in Development Studies* 3: 179-195.

Alem, Y., and J. Colmer. 2013. Don't Worry, Be Happy: The Impact of Climate Variability on the Subjective Well-Being of Smallholder Farmers in Rural Ethiopia. Environment for Development Initiative Discussion Paper Series.

Ali, W.B., K. Deininger, and M. Duponchel (IGC). 2012. Credit Constraints and Agricultural Productivity: Evidence from Rural Rwanda. *Growth Week.*

Association of Ethiopian Microfinance Institutions (AEMFI). 2011. Ethiopian Microfinance Institutions Performance Report, Addis Ababa.

Antwi, G., and J. Antwi. 2010. The Analysis of the Rural Credit Market in Ghana. *International Business and Economics Research Journal* 9(8). http://dx.doi.org/10.19030/iber.v9i8.611

Ayalew, D., and K. Deininger. 2014. Causes and Implications of Credit Rationing in Rural Ethiopia: The Importance of Zonal Variation. *Journal of African Economies* 23(4): 493-527.

Baltagi, B.H. 2005. *Econometric Analysis of Panel Data*. Third edition. England: John Wiley & Sons Ltd.

Belliethathan, S., Y. Tibebe, and W. Girum. 2009. The Impact of Climate Change on Millennium Development Goals (MDGs) and Plan for Accelerated and Sustained Development to End Poverty (PASDEP) Implementation in Ethiopia. Poverty Action Network of Civil Society Organizations in Ethiopia (PANE): A Desk Review. Addis Ababa.

Birhanu, A., and M. Zeller. 2011. Impacts of Rainfall Shock on Smallholders Food Security and Vulnerability in Rural Ethiopia: Learning from Household Panel Data. Department of Agricultural Economics and Social Sciences in the Tropics and Sub-tropics (490a). University of Hohenheim, 70593 Stuttgart, Germany.

Bryan, E., C. Ringler, B. Okoba, C. Roncoli, S. Silvestri, and M. Herrero. 2013. Adapting Agriculture to Climate Change in Kenya: Household Strategies and Determinants. *Journal of Environmental Management* 114: 26-35

Cavatassi, R., L. Lipper, and P. Winters. 2012. Sowing the Seeds of Social Relations: Social Capital and Agricultural Diversity in Hararghe, Ethiopia. *Environment and Development Economics* 17(5):547-578.

Dercon, S. 2002. The Impact of Economic Reforms on Rural Households in Ethiopia: A Study from 1989 to 1995. World Bank, Poverty Dynamics in Africa.

Dercon, S. 2009. Rural Poverty: Old Challenges in New Contexts. *World Bank Research Observer* 24: 1-28.

Deressa, T., R. Hassan, C. Ringler, T. Alemu, and M. Yesuf. 2009. Determinants of Farmers' Choice of Adaptation Methods to Climate Change in the Nile Basin of Ethiopia. *Global Environmental Change* 19: 248-255.

Di Falco, S., M. Veronesi, and M. Yesuf. 2011. Does Adaptation to Climate Change Provide Food Security? A Micro Perspective from Ethiopia. *American Journal of Agricultural Economics* 93(3): 829-846.

Di Falco, S., and E. Bulte. 2011. A Dark Side of Social Capital? Kinship Consumption and Savings. *Journal of Development Studies* 47(8): 1128-1251.

Di Falco, S., and M. Veronesi. 2014. Managing Environmental Risk in the Presence of Climate Change: The Role of Adaptation in the Nile Basin of Ethiopia. *Environmental and Resource Economics* 57(4): 553-577.

Eliotta J., D. Deryngd, C. Müllere, K. Frielere, M. Konzmanne, D. Gertene, M. Glotterf, M. Flörkeg, Y. Wadah, N. Besta, S. Eisnerg, B.M. Feketei, C. Folberthj, I. Fostera, S.N. Goslingk, I. Haddelandl, N. Khabarovm, F. Ludwign, Y. Masakio, S. Olinp, C. Rosenzweig, A.C. Ruaneq, Y. Satohr, E. Schmids, T. Stacket, Q. Tangu, and D. Wisser. 2014. Constraints and Potentials of Future Irrigation Water Availability on Agricultural Production under Climate Change. *Proceedings of the National Academy of Sciences* 111(9): 3239-3244.

Ellis, F. 2000. The Determinants of Rural Livelihood Diversification in Developing Countries. *Journal of Agricultural Economics* 51(2): 289-302.

EM-DAT. 2009. Emergency Events Database. Brussels, Belgium: Center for Research on the Epidemiology of Disasters. Université Catholique de Louvain.

Ethiopian Economics Association (EEA). 2011. Report on the Ethiopian Economy. June 2011.

Fafchamps, M., and J. Pender. 1996. Precautionary Saving, Credit Constraints, and Irreversible Investment: Theory and Evidence from Semiarid India. *Journal of Business and Economic Statistics: Structural Estimation in Applied Microeconomics* 15(2): 180-194.

Fafchamps. M., C. Udry, and K. Czukas. 1998. Drought and Saving in West Africa: Are Livestock a Buffer Stock? *Journal of Development Economics* 55(2): 273-305.

Food and Agriculture Organization (FAO) of the United Nations. 2008. Climate Change Adaptation and Mitigation in the Food and Agriculture Sector. Rome: FAO.

Friedman, M. 1957. *A Theory of the Consumption Function.* Princeton: Princeton University Press.

Gebregziabher, G., R.E. Namara, and H. Stein. 2009. Program evaluation, impact assessment studies and methods. *Agricultural Water Management* 96: 1837-1843.

Gu, C. 2002. *Smoothing Spline ANOVA Models*. New York: Springer.

Guirkinger, C., and S. Boucher. 2008. Credit Constraints and Productivity in Peruvian Agriculture. *Agricultural Economics* 39: 295-308.

Hassan, R., and C. Nhemachena. 2008. Determinants of African Farmers' Strategies for Adapting to Climate Change: Multinomial Choice Analysis. *African Journal of Agricultural and Resource Economics* 2(1): 83-104.

International Monetary Fund (IMF). 2012. The Federal Democratic Republic of Ethiopia: 2012 Article IV Consultation – Staff Report. Country Report No. 12/287, October 2012.

IPCC. 2014. Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151.

Jacoby, H., and E. Skoufias. 1997. Risk, Financial Markets, and Human Capital in a Developing Country. *Review of Economic Studies* 64(3): 311-335.

Komarek, A.M. 2010. Crop Diversification Decisions: The Case of Vanilla in Uganda. *Quarterly Journal of International Agriculture* 49(3): 227-242.

Mishra, A.K., and B.K. Goodwin. 1998. Farm Income Variability and the Off-Farm Labor Supply of Farmers and Their Spouses. *American Journal of Agricultural Economics* 79: 880-887.

Mekonnen, A., and A. Damte. 2011. Private Trees as Household Assets and Determinants of Tree-Growing Behavior in Rural Ethiopia. Environment for Development Discussion Paper 11-14.

Meinzen-Dick, R., B. van Koppen, J. Behrman, Z. Karelina, V.M. Akamandisa, L. Hope, and B. Wielgosz. 2012. Putting Gender on the Map: Methods for Mapping Gendered Farm Management Systems in Sub-Saharan Africa. IFPRI Discussion Paper 1153. Washington, DC: International Food Policy Research Institute (IFPRI).

MoFED. 2008. Dynamics of Growth and Poverty in Ethiopia (1195/96-2004/05).

Mogues, T. 2011. Shocks and Asset Dynamics in Ethiopia. *Economic Development and Cultural Change* 60(1): 91-120.

Moser, C. 1998. The Asset Vulnerability Framework: Reassessing Urban Poverty Reduction Strategies. *World Development* 26(1): 1-19.

Mundlak, Y. 1978. On the Pooling of Time Series and Cross Section Data. *Econometrica* 46(1): 69-85.

Narayan, D., and L. Pritchett. 1999. Cents and Sociability: Household Income and Social Capital in Rural Tanzania. *Economic Development and Cultural Change* 47(4): 871-897.

Paul, B. 2005. Industrial Progress, Rural Credit Market and Crop Choice. University of British Columbia, Canada, V6T 2G9.

Orindi, V., A. Ochieng, B. Otiende, S. Bhadwal, K. Anantram, S. Nair, V. Kumar, and U. Kelkar. 2006. Mapping Climate Vulnerability and Poverty in Africa, edited by P.K. Thornton, P.G. Jones, T. Owiyo, R.L. Kruska, M. Herrero, P. Kristjanson, A. Notenbaert, N. Bekele, and A. Omolo. Report to the Department for International Development, ILRI, Nairobi, Kenya.

Quisumbing, A., N. Kumar, and J. Behrman. 2011. Do Shocks Affect Men's and Women's Assets Differently? A Review of Literature and New Evidence from Bangladesh and Uganda. IFPRI Discussion Paper 01113.

Rahm, M., and W. Huffman. 1984. The Adoption of Reduced Tillage: The Role of Human Capital and Other Variables. *American Journal of Agricultural Economics* 66(4): 405-413.

Seo, N., and R. Mendelsohn. 2008. Animal Husbandry in Africa: Climate Change Impacts and Adaptations. *African Journal of Agricultural and Resource Economics* 2(1): 65-82.

Stiglitz, J.E., and A. Weiss. 1981. Credit Rationing in Markets with Imperfect Information. *American Economic Review* 71(3): 393-410.

Stige, L.C., J. Stave, K. Chan, et al. 2006. The Effect of Climate Variation on Agro-pastoral Production in Africa. *Proceedings of the National Academy of Sciences* 103: 3049-3053.

Swift, J. 1989. Why Are Rural People Vulnerable to Famine? *IDS Bulletin* 20(2): 8-15.

Tadege, A. 2007. Climate Change National Adaptation Program of Action (NAPA) of Ethiopia. National Meteorological Agency (NMA). Addis Ababa.

Tamazian, A., and B. Rao. 2010. Do Economic, Financial and Institutional Developments Matter for Environmental Degradation? Evidence from Transitional Economies. *Energy Economics* 32(1): 137-145.

Teklewold, H., M. Kassie, and B. Shiferaw. 2013. Adoption of Multiple Sustainable Agricultural Practices in Rural Ethiopia. *Journal of Agricultural Economics* 64(3): 597-623.

Vörösmarty, C.J., P.B. McIntyre, M.O. Gessner, D. Dudgeon, A. Prusevich, P. Green, and P.M. Davies. 2010. Global Threats to Human Water Security and River Biodiversity. *Nature* 467(7315): 555-61. doi:10.1038/nature09440

Waha, K., C. Müller, A. Bondeau, J.P. Dietrich, P. Kurukulasuriya, J. Heikne, and H. Lotze-Campen. 2012. Adaptation to Climate Change through the Choice of Cropping System and Sowing Date in Sub-Saharan Africa. *Global Environmental Change* 23(1): 130-143.

Wood, J.S. 2003. Thin Plate Regression Splines. *Royal Statistical Society* 65(Part 1): 95-114.

Wanga, J., R. Mendelsohn, A. Dinar, J. Huang, S. Rozelle, and L. Zhang. 2009. The Impact of Climate Change on China’s Agriculture. *Agricultural Economics* 40(2009): 323-337.

Woolcock, M., and D. Narayan. 2000. Social Capital: Implications for Development Theory, Research, and Policy. *World Bank Research Observer* 15(2): 225-49.

Wooldridge, J.M. 2003. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press.

World Bank. 2005. Ethiopia: Risk and Vulnerability Assessment. Report No. 26275-ET, Human Development Group III, Africa Region.

World Bank. 2013. Doing Business 2013. World Bank 2013 Report.

Yang, D., and H. Choi. 2007. Are Remittances Insurance? Evidence from Rainfall Shocks in the Philippines. *World Bank Economic Review* 21(2): 219-248.

You, G.J., and C. Ringler. 2010. Hydro-economic Modeling of Climate Change Impacts in Ethiopia. International Food Policy Research Institute (IFPRI). Discussion Paper 00960. IFPRI, Washington, DC.

Appendix. Additional Regression Results for Robustness Test

Table A1. Effect of Credit Constraints and Climatic Factors on Off-Farm Self-Employment: A Multivariate Probit Model with Mean Rainfall, Mean Temperature, and Mundlak Effects

Dependent variable: Off_farm self-employment

VARIABLES	coefficient	std.err.
Credit constraint categories		
Unconst.non Borrower (IMR)	0.130	0.149
Quantity constrained Borrower (IMR)	0.266*	0.176
Discouraged Borrower (IMR)	0.073	0.213
Risk rationed Borrower (IMR)	-0.101	0.146
Climate variables		
Mean Rainfall	-0.053***	0.014
Mean Temperature	0.261*	0.176
Mean Temperature sqr	-0.006*	0.004
Household faced drought shock (self-reported)	0.114	0.133
Interaction terms		
Qnty_const * rain_CV	-0.882**	0.345
risk_rashned * rain_CV	-0.759**	0.326
Discouraged * rain_CV	-0.414	0.607
Physical asset and plot characteristics		
Land owned (hectare)	-0.237*	0.159
Tropical Livestock Units (TLU)	0.041	0.175
Own radio (proxy for info.)	0.164	0.202
Household Characteristics		
Age of head	-0.011***	0.004
dummy for female head of the household	0.323	0.284
Dummy for a married head	-0.100	0.263
Household size	-0.150	0.145
Head has no education	-0.227	0.244
Head attended some formal education	-0.410	0.327
Time Average (Mundlak)		
Land owned (time_avg)	0.109	0.194
Head has no education (time_avg)	0.320	0.306

Head attended some formal educ. (time_avg)	0.898**	0.376
Own radio (proxy for info.) (time_avg)	-0.045	0.267
Tropical Livestock Units (TLU) (time_avg)	-0.041	0.176
Household size (time_avg)	0.197	0.147
year dummy	0.449*	0.269
Location factors		
Dummy for West Gojjam	1.895***	0.644
Dummy for South Wollo	-0.0285	0.181
Dummy for North Wollo	-0.403**	0.208
Constant	1.611	1.953
Statistics		
Observations	1140	
Wald chi-square	522.1	
Prob > chi2 =	0	
Log likelihood =	-2632.18	

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

Table A2. Effect of Credit Constraints and Climatic Factors on Crop Diversification Decision: A Multivariate Probit Model with Mean Rainfall, Mean Temperature, and Mundlak Effects

Dependent variable: crop diversification		
VARIABLES	coefficient	std.err.
Credit constraint categories		
Unconst.non Borrower (IMR)	-0.509	0.557
Quantity constrained Borrower (IMR)	4.214*	2.394
Discouraged Borrower (IMR)	-7.670**	2.932
Risk rationed Borrower (IMR)	0.153	0.790
Climate variables		
Mean Rainfall	-0.005	0.013
Mean Temperature	0.165	0.140
Mean Temperature sqr	-0.003	0.003
Household faced drought shock (self-reported)	-0.250*	0.157
Interaction terms		
Qnty_const * rain_CV	0.314	0.308
risk_rashned * rain_CV	-0.032	0.180
Discouraged * rain_CV	-0.333***	0.103
Physical asset and plot characteristics		

plot has flat slope (base cat. = steepy slope)	0.319	0.230
plot has gentle slope	0.367*	0.240
distance_to_plot	0.001	0.002
Land owned (hectare)	-0.061	0.141
Tropical Livestock Units (TLU)	0.163	0.147
Own radio (proxy for info.)	0.029	0.175
Household Characteristics		
Age of head	0.014***	0.005
dummy for female head of the household	0.534**	0.278
Dummy for a married head	-0.256	0.226
Household size	0.015	0.120
Head has no education	-0.340*	0.217
Head attended some formal education	0.122	0.283
Time Average (Mundlak)		
Land owned (time_avg)	-0.374**	0.175
Head has no education (time_avg)	0.361	0.248
Head attended some formal educ. (time_avg)	0.039	0.324
Own radio (proxy for info.) (time_avg)	-0.147	0.230
Tropical Livestock Units (TLU) (time_avg)	-0.167	0.148
Household size (time_avg)	-0.007	0.122
year dummy		
Location factors		
Dummy for West Gojjam	-0.660	0.592
Dummy for South Wollo	0.187	0.305
Dummy for North Wollo	-0.284	0.273
Constant	0.354	3.440
Statistics		
Observations	1140	
Wald chi-square	522.1	
Prob > chi2 =	0	
Log likelihood =	-2632.177	

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

Table A3. Effect of Credit Constraints and Climatic Factors on Soil Conservation and Planting Trees: A Multivariate Probit Model with Mean Rainfall, Mean Temperature, and Mundlak Effects

Dependent variable: Soil Conservation and Planting Trees		
VARIABLES	coefficient	std.err.
Credit constraint categories		
Unconst.non Borrower (IMR)	-0.447	0.468
Quantity constrained Borrower (IMR)	-1.152	2.004
Discouraged Borrower (IMR)	-6.033**	2.741
Risk rationed Borrower (IMR)	-0.494	0.692
Climate variables		
Mean Rainfall	0.017*	0.012
Mean Temperature	0.210*	0.128
Mean Temperature sqr	-0.004*	0.003
Household faced drought shock (self-reported)	-0.068	0.139
Interaction terms		
Qnty_const * rain_CV	-0.262	0.280
risk_rashned * rain_CV	-0.081	0.156
Discouraged * rain_CV	-0.038	0.128
Physical asset and plot characteristics		
plot has flat slope (base cat. = steepy slope)	0.323*	0.188
plot has gentle slope	0.483**	0.200
distance_to_plot	0.003**	0.002
Land owned (hectare)	0.110	0.116
Tropical Livestock Units (TLU)	-0.060	0.129
Own radio (proxy for info.)	0.128	0.154
Household Characteristics		
Age of head	0.006*	0.004
dummy for female head of the household	0.148	0.250
Dummy for a married head	-0.083	0.207
Household size	0.293***	0.106
Head has no education	-0.092	0.189
Head attended some formal education	0.324	0.251
Time Average (Mundlak)		
Land owned (time_avg)	-0.001	0.141
Head has no education (time_avg)	0.333*	0.216

Head attended some formal educ. (time_avg)	-0.181	0.286
Own radio (proxy for info.) (time_avg)	-0.386*	0.203
Tropical Livestock Units (TLU) (time_avg)	0.056	0.130
Household size (time_avg)	-0.247**	0.108
year dummy	0.280*	0.215
Location factors		
Dummy for West Gojjam	-0.577	0.522
Dummy for South Wollo	-0.788***	0.150
Dummy for North Wollo	-0.068	0.229
Constant	0.862	2.861
Statistics		
Observations	1140	
Wald chi-square	522.1	
Prob > chi2 =	0	
Log likelihood =	-2632.177	

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

Table A4. Effect of Credit Constraints and Climatic Factors on Depleting Productive Assets: A Multivariate Probit Model with Mean Rainfall, Mean Temperature, and Mundlak Effects

Dependent variable: Depleting Productive Assets		
VARIABLES	coefficient	std.err.
Credit constraint categories		
Unconst.non Borrower (IMR)	1.556***	0.490
Quantity constrained Borrower (IMR)	1.898	1.871
Discouraged Borrower (IMR)	2.189	2.407
Risk rationed Borrower (IMR)	1.034	0.716
Climate variables		
Mean Rainfall	0.027**	0.014
Mean Temperature	-0.071	0.140
Mean Temperature sqr	0.003	0.003
Household faced drought shock (self-reported)	-0.127	0.110
Interaction terms		
Qnty_const * rain_CV	0.565**	0.277
risk_rashned * rain_CV	0.467***	0.159

Discouraged * rain_CV	0.871*	0.475
Physical asset and plot characteristics		
plot has flat slope (base cat. = steepy slope)	-0.004	0.183
plot has gentle slope	-0.272	0.197
distance_to_plot	-0.002*	0.002
Land owned (hectare)	0.233**	0.116
Tropical Livestock Units (TLU)	0.276**	0.133
Own radio (proxy for info.)	0.082	0.158
Household Characteristics		
Age of head	0.002	0.004
dummy for female head of the household	0.078	0.259
Dummy for a married head	0.317	0.217
Household size	-0.143	0.107
Head has no education	0.180	0.190
Head attended some formal education	0.333	0.257
Time Average (Mundlak)		
Land owned (time_avg)	0.087	0.143
Head has no education (time_avg)	-0.223	0.221
Head attended some formal educ. (time_avg)	-0.166	0.291
Own radio (proxy for info.) (time_avg)	-0.190	0.207
Tropical Livestock Units (TLU) (time_avg)	-0.281**	0.134
Household size (time_avg)	0.180*	0.109
year dummy		
Location factors		
Dummy for West Gojjam	-1.735***	0.619
Dummy for South Wollo	-0.015	0.155
Dummy for North Wollo	0.779***	0.219
Constant	-8.501***	2.614
Statistics		
Observations	1140	
Wald chi-square	522.1	
Prob > chi2 =	0	
Log likelihood =	-2632.177	

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

Table A5. Effect of Credit Constraints and Climatic Factors on Investing in Small-Scale Irrigation: A Multivariate Probit Model with Mean Rainfall, Mean Temperature, and Mundlak Effects

Dependent variable: Investing in Small-scale Irrigation		
VARIABLES	coefficient	std.err.
Credit constraint categories		
Unconst.non Borrower (IMR)	0.313**	0.156
Quantity constrained Borrower (IMR)	0.574	0.504
Discouraged Borrower (IMR)	0.701***	0.239
Risk rationed Borrower (IMR)	0.069	0.158
Climate variables		
Mean Rainfall	-0.016	0.014
Mean Temperature	0.052	0.141
Mean Temperature sqr	-0.001	0.003
Household faced drought shock (self-reported)	-0.302	0.246
Interaction terms		
Qnty_const * rain_CV	-0.447	1.109
risk_rashned * rain_CV	0.123	0.281
Discouraged * rain_CV	-4.581	283.391
Physical asset and plot characteristics		
plot has flat slope (base cat. = steepy slope)	0.663***	0.284
plot has gentle slope	0.368	0.298
distance_to_plot	-0.001	0.002
Land owned (hectare)	-0.093	0.133
Tropical Livestock Units (TLU)	-0.357**	0.166
Own radio (proxy for info.)	-0.083	0.189
Household Characteristics		
Age of head	-0.006*	0.004
dummy for female head of the household	-0.306	0.267
Dummy for a married head	-0.282	0.234
Household size	0.120	0.112
Head has no education	0.103	0.217
Head attended some formal education	0.526*	0.315
Time Average (Mundlak)		
Land owned (time_avg)	0.143	0.171
Head has no education (time_avg)	0.161	0.267

Head attended some formal educ. (time_avg)	-0.360	0.357
Own radio (proxy for info.) (time_avg)	0.227	0.245
Tropical Livestock Units (TLU) (time_avg)	0.352**	0.167
Household size (time_avg)	-0.139	0.115
year dummy	-0.070	0.226
Location factors		
Dummy for West Gojjam	-0.065	0.634
Dummy for South Wollo	0.724***	0.175
Dummy for North Wollo	0.601***	0.193
Constant	-0.459	1.686
Statistics		
Observations	1140	
Wald chi-square	522.1	
Prob > chi2 =	0	
Log likelihood =	-2632.177	

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