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Adaptation to climate risk and food security

Evidence from smallholder farmers in Ethiopia

ADAPTATION TO CLIMATE RISK AND FOOD SECURITY: EVIDENCE FROM SMALLHOLDER FARMERS IN ETHIOPIA

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Adaptation to Climate Risk and Food Security: Evidence from Smallholder Farmers in Ethiopia

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Abstract

This paper explores the impact of climate risk on the adoption of risk decreasing practices and other input choices and evaluates their impact on subjective and objective measures of household welfare (namely net crop income and a food insecurity indicator). The analysis is conducted primarily using a novel data set that combines data from the large-scale and representative Ethiopia Socioeconomic Survey (ERSS), 2011/12 with historical climate and biophysical data. We employ a multivariate probit model on plot level observations to model simultaneous and interdependent adoption decisions and utilize a conditional mixed process estimator (CMP) and instrumental variable (IV) method for the impact estimates. Findings show that there is interdependency between the adoption decisions of different farm management practices which may be attributed to complementarities or substitutability between the practices. Greater riskiness, reflected in the coefficients of variation and higher temperature, increases use of risk reducing inputs such as climate-smart agriculture (CSA) inputs, but decrease use of modern inputs such as chemical fertilizer. Even if higher climate risk does generate higher incentive to adopt, results also confirm the importance of other conventional constraints to adoption that need to be addressed. Yield enhancing inputs such as chemical fertilizer and improved seed are mainly adopted by wealthier households and households having access to credit and extension services whereas risk reducing inputs are frequently used by households with lower level of wealth and limited access to credit and households with stable land tenure. Moreover, the CMP and IV estimations showed that the adoption of CSA and modern inputs have positive and statistically significant impacts on the objective measure of food security (net crop income) but no impact is observed for the subjective food security indicator.

Keywords: Climate change, adaptation, impact, multivariate probit, instrumental variable, Ethiopia, Africa

JEL Classification: Q01, Q12, Q16, Q18

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1. Introduction

Warming of the climate system is unequivocal, as is now evident from observations of increases in global average air and ocean temperatures, widespread melting of snow and ice, and the rising global average sea level. Climate change is expected to have negative impacts on agriculture in many regions, including the reduction of average yields in the longer term, as well as potentially increasing yield variability and crop failures through the greater frequency and intensity of extreme weather events such as droughts and floods (e.g., IPCC 2011; Challinor et.al. 2010). From recent studies on vulnerability and poverty in Africa, Ethiopia turned out to be one of the countries both most vulnerable to climate change and with the least capacity to respond (Orindi et al., 2006; Stige et al., 2006). Harvest failure due to weather events is the most important cause of risk-related hardship of Ethiopian rural households, with adverse effects on farm household consumption and welfare (Dercon 2004, 2005). Reducing the vulnerability of agricultural systems to climate change is thus an important priority for agricultural development and to protect and improve the livelihoods of the poor and to ensure food security (Bradshaw et al., 2004; Wang et al., 2009).

Many environmental issues involve endogenous risks, thus human actions and reactions can change the chances that good things happen and bad things do not (Ehrlich and Beker, 1972). Endogenous risk addresses the idea that individuals have some personal control over the set of probabilities and outcomes that define the relevant states of the world. In this framework, it is possible to distinguish between self-protection that represents private investments to increase the probability that a good state occurs and self-insurance that are expenditures to reduce severity of the bad state if it is realized. In the case of climate change self-protection is more commonly referred to as mitigation and self-insurance as adaptation. In the endogenous risk perspective, mitigation and adaptation are considered two risk reduction strategies for risks associated with climate change (Hanley et al., 2007).

The focus of our research is on climate adaptation approaches as defined by IPCC 2007: “Adaptation to climate change refers to adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities”. These may include both on and off farm activities. One of the most important ways to reduce vulnerability to climate variability is increasing the physical resilience of the system (FAO 2011; IPCC 2011). Farmers, for instance, may invest in soil and water conservation measures including conservation agriculture in an attempt to retain soil moisture (Kurukulasuriya and Rosenthal, 2003; McCarthy et al., 2011); modify planting times and change to crop varieties resistant to heat and drought (Phiri and Saka, 2008); adopt new cultivars (Eckhardt et al., 2009); change the farm portfolio of crops and livestock (Howden et al., 2007); and shift to non-farm livelihood sources (Morton, 2007). Which of these actually contribute to adaptation depends on the locally specific effects climate change has and will have, as well as agro-ecological conditions and socio-economic factors such as market development. Those that meet these criteria may be considered Climate Smart Agriculture (CSA)[3] practices. Frequently sustainable land management (SLM) practices fall into this category, due to their effects on increasing resilience (FAO, 2013).

Given our dataset, this paper investigates the adoption and impact of a set of potentially risk reducing inputs (which we refer hereafter as CSA inputs) implemented in the field (legume intercropping, anti-erosion measures, and the use of organic fertilizer) that are high priorities in Ethiopia's national agricultural plan. They are considered effective in terms of increasing the resilience of the agricultural system and of reducing exposure to climate shocks, and in this way contribute to adaptation. We also consider improved varieties and use of chemical fertilizer (referred hereafter as modern inputs), which are two practices aimed primarily at improving average yields, though with uncertain benefits in terms of adapting to climate change and/or reducing risk to current climate stresses. Conservation agriculture is also high in Ethiopia's national agricultural priority plan and is considered to have adaptation potential but we lack data on these practices and as a result they are not included in our analysis[4]. Despite the growing policy interest and increasing resources dedicated to promoting these agricultural practices in many regions, including Ethiopia, and the consolidated findings which validate the fact that farmers who actually did implement agricultural adaptation strategies are indeed getting benefits in terms of food security (Tenge et al., 2004; Kassie et al., 2010; Wollni et al., 2010), the adoption rate of such practices is generally quite low (Teklewold et al., 2013). This paper addresses the knowledge gap, shedding new light on the topic through a careful analysis of farmers' incentives and conditioning factors that hinder or accelerate adoption of these practices to deal with a multitude of climate risks.

Our contributions to the existing literature are fourfold: firstly our analysis uses a comprehensive and large plot-level survey with rich socio-economic information that is nationally representative and merged with geo-referenced climatic information. This allows us to evaluate the role of climatic and bio-physical variables in determining farmers' adoption decisions and consequently the impact on food security by exploiting exogenous variation in weather outcomes over time and between administrative areas. We argue that climate variability and other shifts in recent climate patterns are major determinants of farm agricultural production choices in rural areas as a result of the dependence on agriculture for subsistence consumption and livelihoods. This is distinct from the literature which

[3] Climate smart agricultural practices are defined as those practices that increase adaptive capacity and resilience of farm production in the face of climate shocks thereby improving food security, and which can also mitigate GHG emissions, mainly through increased carbon sequestration in soils (FAO, 2011)

[4] Set of agricultural practices considered in this paper is mainly driven by the availability of data. For instance our data lacks information on some risk decreasing input like conservation agriculture and thus are not included in our analysis.

examines the effects of weather shocks using the level of rainfall or deviation from its mean. Whilst weather shocks are clearly important, we also give particular attention to long term climate variability, as a proxy for expectations about future uncertainty. Secondly, we provide a more comprehensive and rigorous analysis in which adoption of a mix of practices is modelled simultaneously using a method that takes into account the interdependence between different practices. Thirdly, our paper estimates the relationship between food security and adoption of agricultural practices in Ethiopia by using a subjective food insecurity measure and objective measures such as crop net income.

The use of subjective measures, such as self-reported poverty (Deaton, 2010), perceptions of economic welfare (Ravallion and Lokshin, 2002) and perception of the respondents' own food security status (Kassie et al., 2010) instead of objective measures such as per capita consumption or income is becoming a growing practice. Finally, we estimate the causal impact of adoption of the agricultural practices on the food security indicator using instrumental variables techniques (IV) improved using the Lewbel (2012) method as well as conditional recursive mixed process (CMP) estimators as proposed by Roodman (2011) taking into account both simultaneity and endogeneity and obtaining consistent estimates for recursive systems in which all endogenous variables appear on the right-hand-side. While technologies are often intended to be productivity enhancing, value-adding and cost saving, not all technologies are beneficial and responsive to the needs of different segments of the expected users and perform as expected in different climate regimes.

The paper is structured as follows. Section 2 provides country background and a review of the existing literature on adoption of agricultural strategies, climate change and food security. Data sources and descriptive results are presented in Section 3. In Section 4 the conceptual framework and the econometric strategies are illustrated. The main analytical results are presented and discussed in Section 5 while Section 6 concludes by providing the key findings and the policy implications.

2. Background and overview of literature

2.1 Background and motivation

In Sub-Saharan Africa, three quarters of the population reside in rural areas, and rely on agriculture for securing their livelihood, increasing their welfare, accessing food and guaranteeing their basic needs. Despite this high dependence on agriculture, the contribution of the sector to total GDP was only 13 percent in 2010 (WDI, 2010). Notwithstanding the food and financial crisis as well as the adverse effects of climate change, investing in agriculture can be 2 to 3 times more effective at raising the income and consumption of poor households than growth that can be originated from other sectors of the economy (de Janvry, 2010).

Ethiopia, with a population of 90.9 million and a population growth rate of 3.2 percent (a doubling time of 22 years) in 2011, faces increased levels of food insecurity. Ethiopian agriculture is heavily dependent on natural rainfall, with irrigation agriculture accounting for around 4 percent of the country's total plots (CIA, 2011). Thus, the amount of rainfall and average temperature as well as other climatic factors during the growing season are critical to crop yields and food security problems. As highlighted by several studies Ethiopia is one of the countries both most vulnerable to climate change and with the least capacity to respond (Orindi et al., 2006; Stige et al., 2006). With low diversified economies and reliance on rain fed agriculture, Ethiopia's agricultural production has been closely associated with the climate. The World Bank (2006) reported that catastrophic hydrological events such as droughts and floods have reduced Ethiopia's productive performance of the agricultural sector over the last forty years and large areas of Ethiopia are plagued by food insecurity. This has been confirmed by the overwhelming effects of various prolonged droughts in the twentieth century and recent flooding.

According to Funk et al. (2012), Ethiopia receives most of its rain between March and September. Rains begin in the south and central parts of the country during the Belg (short rainy) season, then progress northward, with central and northern Ethiopia receiving most of their precipitation during the Kiremt (long rainy) season. Rainfall totals of more than 500 mm during these rainy seasons typically provide enough water for viable farming and pastoral pursuits. Between the mid-1970s and late 2000s, Belg and Kiremt rainfall, based on quality controlled station observations, decreased by 15–20 percent across parts of southern, south-western, and south-eastern Ethiopia (Funk et al., 2012). During the past 20 years, the areas receiving sufficient Belg rains have contracted by 16 percent, exposing densely populated areas of the Rift Valley in south-central Ethiopia to near-chronic food insecurity. The same occurred for the Kiremt season. Approximately 20.7 million people live in these affected zones (Funk et al., 2012). Poor long cycle crop performance in the south-central and eastern midlands and highlands could directly affect the livelihoods of many of these people, while adding pressure to national cereal prices. The FEWS NET (2011) studies of Ethiopia highlight a crucial coincidence between densely-populated areas and observed declines in rainfall. It appears likely that the combination of population growth, land degradation, and frequent droughts will result in more frequent food-related crises.

As a consequence, a significant long-term social protection program known as the Productive Safety Net Programme (PSNP) was implemented in Ethiopia in 2007 in response to experiences from a series of drought-related disaster responses during the late 1990s and early 2000s (Pierro and Desai, 2008). When there is a food emergency, the PSNP is able to provide immediate cash payments that may be sufficient to save lives even in the case of very severe droughts. However, these payments may not be sufficient to restore livelihoods (World Bank, 2006b). Moreover, a drawback of this arrangement is that it perpetuates dependence on post-drought government assistance with accompanying moral hazard. Micro-insurance to cover, for example, life and health is widespread in developing countries, but applications for catastrophic risks to crops and property are in the beginning phases (see Morelli et al. (2010) for a review on micro-insurance and climate change).

In addition, there are considerable efforts by national and international organizations to encourage farmers to invest in sustainable agricultural systems, to build the physical resilience of the system, and to reduce vulnerability to climate variability. Ethiopian farmers often engage in sustainable land management (SLM) practices which maintain and enhance soil productivity over time to adapt to this climate variability. These practices include soil fertility treatments such as application of chemical and organic fertilizers, legume intercropping, soil and water conservation measures such as contour ridging, terracing or providing ground cover through mulching, use of plants and leaving crop residues. Despite considerable efforts to promote these technologies, the adoption of many recommended measures is minimal, and soil degradation continues to be a major constraint to productivity growth and sustainable intensification. A better understanding of constraints that condition farmers' adoption behaviour for these practices is therefore important for designing promising pro-poor policies that could stimulate their adoption and increase productivity.

2.2 Overview of literature

A growing part of the literature on the impact of climate change and climate related adaptation strategies on crop yield and food security is largely based on either agronomic models or Ricardian analysis to investigate the degree of these impacts (e.g. Deressa, 2006; Deressa and Hassan, 2010; Kurukulasuriya and Rosenthal, 2003; Seo and Mendelsohn, 2009; Wang et al., 2009). In the first case, after estimating directly the impacts of climate change on crop yields, they use the results from the previous model in behavioural models that simulate the relevant soil-plant-atmospheric components that determine plant growth and yield (e.g., Gregory et al., 1999). The Ricardian approach (pioneered by Mendelsohn et al., 1994), on the other hand, assumed that farmers have been adapting optimally to climate in the past and adaptation choices do not need to be modelled explicitly. Land values, for instance, at a particular point in time are assumed to include future climate changes and potential adaptation measures.

A limitation of this approach is that adaptation is an endogenous decision and that unobservable heterogeneity (e.g., differences in farmers' abilities) may lead to biased estimates. Therefore, Ricardian cross-sectional analysis fails to identify the key adaptation strategies that reduce the implication of climate on food production (Di Falco et al., 2011). To overcome this drawback Di Falco et al. (2011) tried to disentangle the productive implications of adaptation to climate change. Using a survey conducted on 1,000 farm households located within the Nile Basin of Ethiopia in 2005, they found that there are significant and non-negligible differences in food productivity between the farm households that adapted and those that did not adapt to climate change. They also found that adaptation to climate change increases food productivity.

There is a large body of literature on the theoretical and empirical impacts of production risk on farmers' *ex ante* production technology choices (e.g., Fafchamps, 1999, 1992; Chavas and Holt 1996; Sadoulet and de Janvry, 1995). This literature indicates that there are several barriers to technology adoption ranging from lack of insurance and limited credit access to price risk. Pope and Kramer (1979) however considered inputs that could be both risk-increasing and risk-decreasing. In general, the risk-decreasing input such as CSA practices increases where producers are more risk-averse; overall production impacts depend on stochastic complementarity or substitutability amongst inputs. In the two-input case with a standard Cobb-Douglas production function, with only one input that is risk decreasing (and the other risk "neutral"), total production declines with increases in exogenous risk, as the decreases in the risk-"neutral" input offset increases in the risk-decreasing input. This is important in the context of climate change.

There are however few empirical studies that explicitly evaluate the impact of climate risk on the adoption of risk decreasing practices or other input choices (e.g. Kassie et al., 2010; Rosenzweig and Binswanger, 1993; Heltberg and Tarp, 2002). Estimation of the impact of climate change on food production on the country, regional, and global scale has been done using either agronomic or Ricardian approach (e.g., McCarthy et al., 2001; Deressa, 2006). The aggregate nature of these studies, however, makes it very difficult to provide insights in terms of effective adaptation strategies at the micro or farm household level (e.g., Rosenzweig and Parry, 1994). A study conducted by Yemenu and Chemeda (2010) and using thirty three years of weather record data on central highlands of Ethiopia indicated higher probabilities of dry spell occurrences during the shorter season (Belg), but the occurrences of the same in the main rainy season (Kiremt) were very minimal. Therefore, the authors found that a considerable attention to maximizing crop harvest during the main rainy season is sensibly important.

Aside from climate risk, several other factors have also been identified to account for the use of key adaptation strategies including high up-front costs but delayed benefits (McCarthy, 2010; Sylwester, 2004) and credit and insurance market imperfections (Carter and Barrett, 2006). McCarthy et al. (2011) synthesized recent empirical literature on factors affecting the on adoption of SLM practices: investment costs, variable and maintenance costs, opportunity costs, transactions costs, and risk costs.

Overall micro evidence on the impact of rainfall, temperature, and climate related adaptation strategies on crop yield and food security is very scarce. This paper aims to contribute to the literature on climate change on agriculture by providing a micro viewpoint, nationally representative, on the topic of adaptation and food security taking into account climate variability. In contrast with the previous literature, we have the use of actual and reliable rainfall and temperature data at the enumeration area level from 1989 to 2011. Based on the empirical and theoretical literature review, we expect that increased climate risk will reduce incentives for agricultural technology adoption in general, but the risk reducing benefits associated with key adaptation strategies like CSA could generate positive incentives for adoption of this specific type of technology, although the effect will depend on context-specific parameters.

Even if higher climate risks do generate higher incentives to adopt, there are also several other constraints to adoption that need to be addressed, which include the capacity to finance key adaptation strategies, the degree to which benefits from adoption are delayed, the risk reduction (resilience) benefits associated with adoption and the capacity to engage in collective action.

3. Data description and descriptive statistics

3.1 Data

The main data sets used are cross-sectional datasets from the Ethiopia Socioeconomic Survey (ERSS), 2011/12 and Ethiopia Rural Household Survey (ERHS), 2009. The ERSS survey is a collaborative project between the Central Statistics Agency of Ethiopia (CSA) and the World Bank Living Standards Measurement Study- Integrated Surveys of Agriculture team (LSMS-ISA). The objective of the ERSS is to collect multi-topic household level data with a special focus on improving agriculture statistics and the link between agriculture and other household income activities. The sample consists of 3,969 household and about 32,000 plots. The ERSS sample is drawn from a population frame that includes all rural and small town areas in Ethiopia except for three zones of Afar and six zones of the Somali region. ERSS is integrated with the CSA's Annual Agricultural Sample Survey (AgSS) and the rural sample is a sub-sample of the AgSS. The ERSS sample is designed to be representative of rural and small town areas of Ethiopia. The sample design is a stratified, two-stage design where the regions of Ethiopia serve as the strata. Quotas were set for the number of enumeration areas (EAs) in each region to ensure a minimum number of EAs are drawn from each region. The total number of EA included in the survey is 353. Detailed information on the sampling strategy is reported in the World Bank (2013) report.

The survey was designed to be implemented in three rounds following the AgSS field schedule. The first round took place between September and October 2011. In this round, the post-planting agriculture questionnaire was administered. The second round took place between November and December 2011 when the livestock questionnaire was administered. The third round took place from January through March 2012 when the household, community and post-harvest agriculture questionnaires were administered. The 2011 survey location and land area of the plots are also recorded using handheld global positioning system (GPS) devices which then created the possibility of linking household level data with geographic information system (GIS) databases. The community questionnaire is administered in each of the enumeration areas visited as part of the survey. The questionnaire solicits information on a range of community characteristics, including religious and ethnic background, physical infrastructure, access to public services, economic activities, communal resource management, organization and governance, investment projects, and local retail price information for essential goods and services.

The 2011 ERSS survey data included geo-referenced household and EA level Latitude and Longitude coordinates which allowed us to extract the remote sensing time series indicators such as community level rainfall cumulative sum and average temperature (1983-2012). While the amount of rainfalls have been estimated using Africa Rainfall Climatology version 2 (ARC2) from National Oceanic and Atmospheric Administration (NOAA), average minimum and maximum temperature have been calculated using ECMWF ERA INTERIM reanalysis model data.[5] Whilst previous studies have relied on the use of meteorological data provided by the Ethiopian Meteorological service, the number of missing observations, or observations which are recorded as zero on days that there are no records, is of concern. This is exacerbated by the serious decline in the past few decades in the number of weather stations around the world that are reporting. Lorenz and Kuntsman (2012) show that since 1990 the number of reporting weather stations in Africa has fallen from around 3,500 to around 500. With 54 countries in the continent this results in an average of below 10 weather stations per country. This results in an increase in the error that these variables are measured with. If this measurement error is classical i.e. uncorrelated with the actual level of rainfall being measured, then our estimates of the effect that these variables have will be biased towards zero.

By merging the ERSS data with historical data on rainfall and temperature at the community level, we create a unique data set allowing for microeconomic analysis of climate in Ethiopia.

This paper also makes use of the final round (2009) of the Ethiopian Rural Household Survey (ERHS) for limited descriptive analysis, as this year is the only year to contain questions on the use of agricultural practices. The ERHS was conducted by Addis Ababa University in collaboration with the Centre for the Study of African Economies (CSAE) at the University of Oxford and the International Food Policy Research Institute (IFPRI) in seven rounds between 1994 and 2009 (see Dercon and Hoddinot, 2004). It is important however to point out that this data set, unlike that of 2011, does not contain geo reference information which are critical to extract climate information. It also should be noted that ERHS is not nationally representative because the sample excludes pastoral households and urban areas and only covers 15 villages. Therefore we restrict the use the 2009 data set only for static comparison purpose at the descriptive level.

3.2 Variables and Descriptive statistics

We conducted the analysis at plot level, on the five major crops grown in Ethiopia: maize, barley, sorghum, teff and wheat. For each plot, the land holder reported the type of land practice and inputs, such as legume-intercropping, chemical fertilizer, organic fertilizer, improved seeds, and anti-erosion measures used during the sample year.

[5] We decided to use ARC2 rather than ECMWF data for rainfalls given the fact that ARC2 have a finest resolution (0.1 degrees vis a vis 0.25 degrees).

Fertilizer, either chemical or organic, is used in around half of major food grain plots. For example, fertilizer is applied in about 68 percent of maize and wheat plots and 66 percent of teff plots. It is also used in about 56 percent of barley plots. The least commonly fertilized of the top five food grain plots is sorghum with about 28 percent of the plots receiving fertilizer application. As shown in Table 1, the two modern agricultural inputs used by farmers are chemical fertilizer and improved seeds[6]. The use of chemical fertilizer is on average 33 percent, remaining mainly constant between 2009 and 2011[7]. It is worth noting the large difference in the adoption rates across regions from the two years. According to the 2009 ERHS survey, in Tigray only 8 percent of plots are treated with chemical fertilizer, while in the same region (Tigray) in 2011 there is a widespread use of this input (52 percent) with respect to other regions. This mismatching is likely due to the fact that ERHS survey is not statistically representative and only 15 villages are included.

Improved seed coverage is very low (9.3 percent in the 2009 ERHS and 8.2 percent in the 2011 ERSS), especially in Tigray where only the 1.4 percent of plots in the 2009 ERHS and 3.7 percent of plots in the 2011 ERSS use high-yield-crop varieties. Also the adoption of legume inter-cropping is very low. Despite the potential advantages of legume inter-cropping, such as reduction in the risk of crop failure, soil fertility increase (leguminous intercrops fix nitrogen in the soil), land use maximization, and diets becoming healthier, only about 1.6 percent of plots in the 2009 ERHS and 5.3 percent of the plots in the 2011 ERSS are treated with this practice. The use of organic fertilizer (manure and compost) is on about 26 percent of the major crop plots in the two periods, with a larger adoption in Tigray (38,8 and 36.7 percent in the 2009 ERHS and 2011 ERSS, respectively) followed by SNNP (36.4 percent) regions in the 2009 ERHS and Amhara (26.2 percent) in the 2011 ERSS. Finally, the adoption of anti-erosion measures in Ethiopia is very low.

Despite the huge potential for climate change mitigation and adaption, less than 5 percent of the plots are treated by the anti-erosion measures. The adoption rate is slightly prevalent in Tigray (15.92 percent) which is not surprising given the landscape of the region[8].

[6] It is also common to use herbicides and insecticides to control weeds, fungus, pests and insects. Herbicides or insecticides are used in close to half of teff and wheat plots and 1 in 4 plots of barley, maize and sorghum.

[7] The information available refer to the use of DAP and UREA fertilizer, with a larger adoption of DAP (average in 2011, 11.33 percent) with respect to UREA (average in 2011, 8.60 percent) in all regions.

[8] The comparison between adoption rates of anti-erosion measures in the 2009 ERHS and 2011 ERSS is not reported in Table 1, which is due to the lack of comparability among the two surveys. In the 2009 data, there is detailed information on soil conservation measures that include indigenous stone bunding, 'Fanya juu' (meaning "throw the soil up" in Kiswahili) terraces, strip conning and other specific measures (10 categories) while only four common ways of preventing the field from erosion are in the 2011 dataset (terracing, afforestation, water catchments and plough along the contour).

Table 1. Adoption rate of soil conservation practices and inputs use at field level, by region

	Chemical fertilizer		Improved seeds		Organic fertilizer		Legume inter-cropping		Anti-erosion measures
	2009	*2011*	*2009*	*2011*	*2009*	*2011*	*2009*	*2011*	*2011*
Tigray	7.79	52.07	1.43	3.74	38.11	36.78	3.61	0.32	15.92
Amhara	26.65	28.84	1.74	9.16	15.7	26.21	2.09	3.29	8.31
Oromia	50.91	35.52	11.08	8.71	23.16	23.24	1.26	4.45	0.4
SNNP	15.31	39.42	17.53	12.46	36.49	18.99	0.97	7.04	2.32
Other regions	-	14.03	-	4.38	-	29.14	-	11.33	0
All	32.17	33.11	9.34	8.29	25.12	25.79	1.57	5.34	4.77

The adoption rate changes when we look at the use of multiple practices at the same time on the same plots. Table 2 reports the proportions of plots treated under different practices for the five major crops cultivated in Ethiopia (maize, barley, sorghum, teff and wheat). Of 9,942 plots, about 44 percent did not receive any of the treatments, while the simultaneous adoption of the five practices is not present in any of the plots selected. Only 0.06 percent of plots adopt simultaneously the three CSA measures of legume-intercropping, organic fertilizer and anti-erosion measures. Modern inputs, chemical fertilizers and improved seeds are used all together in 4 percent of the plots. The bottom line is that the proportions of adoption of a given practice in combination with other practices are relatively small (see Table 2).

Table 2. Descriptive summary of adoption of multiple practices

Chemical fertilizer	Improved seeds	Legume-intercropping	Organic fertilizer	Anti-erosion measures	N	Percent
0	0	0	0	0	4,334	43.59
0	0	0	0	1	135	1.36
0	0	0	1	0	1,472	14.81
0	0	0	1	1	85	0.85
0	0	1	0	0	253	2.54
0	0	1	0	1	1	0.01
0	0	1	1	0	173	1.74
0	0	1	1	1	6	0.06
0	1	0	0	0	108	1.09
0	1	0	0	1	9	0.09
0	1	0	1	0	56	0.56
0	1	0	1	1	4	0.04
0	1	1	0	0	9	0.09
0	1	1	1	0	4	0.04
0	1	1	1	1	1	0.01
1	0	0	0	0	1,913	19.24
1	0	0	0	1	119	1.2
1	0	0	1	0	504	5.07
1	0	0	1	1	73	0.73
1	0	1	0	0	27	0.27
1	0	1	1	0	23	0.23
1	1	0	0	0	419	4.21
1	1	0	0	1	22	0.22
1	1	0	1	0	139	1.4
1	1	0	1	1	19	0.19
1	1	1	0	0	29	0.29
1	1	1	1	0	5	0.05
				Total	9,942	100

Table 3 presents descriptive statistics for the key dependent variables – the reported level of household welfare – for the analyzed period. We use both an objective measure such as net crop income and a subjective measure such as self-reported food security status of the household (see e.g. Deaton 2010). We use as a subjective measure the household perception of having faced a situation where not enough food to feed the household was available. Here the core concept of food security refers to the pioneering work of Sen (1982) on food “entitlements”. As an outcome variable, we use a binary variable which is 1 if the household, in the last 12 months, faced a situation where not enough food to feed the household was available and 0 otherwise.

There is a statistically significant difference in terms of the food insecurity indicator and net crop income between adopters and non adopters of the different agricultural practices, with the only exception referring to the adoption of improved seeds. According to both the subjective and the objective measure, the adoption of the different strategies improves food security status and increases crop income, respectively.

Notwithstanding, legume inter-cropping increases the problem of food security, contrasting the effect of organic and chemical fertilizer, improved seeds and anti-erosion measures (Table 5). Looking also at the broader adoption category level, descriptive results show that adopters of modern inputs (chemical fertilizer or improved seed) as well as CSA (organic fertilizer or anti-erosion measures or legume intercropping) seem to enjoy higher crop income and better food security status compared to the non-adopters.

However, because adoption is endogenous, a simple comparison of the outcome indicators of adopter and non-adopters has no causal interpretation. Thus, observed and unobserved factors, such as differences in household and/or plot characteristics and endowments can determinate the above differences.

Table 3. Subjective food insecurity indicator and net crop income by adoption status

	Food insecurity indicator		Net crop income	
	Mean	Std. Err.	Mean	Std. Err.
Chemical fertilizer				
No	0.29	0.005	4901.22	27.882
Yes	0.27	0.007	5285.69	55.112
Difference	0.02 (2.23)**		-384.47(-6.93) ***	
Improved seed				
No	0.29	0.004	5038.13	27.01
Yes	0.27	0.015	5011.73	98.80
Difference	0.013 (0.80)		26.39(0.27)	
Legume intercropping				
No	0.28	0.004	5016.04	26.49
Yes	0.34	0.020	5446.31	129.82
Difference	-0.054 (-2.71)***		-430.26(-3.72) ***	
Organic fertilizer				
No	0.29	0.005	4945.18	27.45
Yes	0.26	0.008	5279.21	63.38
Difference	0.028 (2.75) ***		-334.02(-5.60) ***	
Anti-erosion measures				
No	0.29	0.004	4966.75	144.04
Yes	0.18	0.017	4233.58	53.58
Difference	0.116 (5.45)***		733.16(4.81) ***	
Modern inputs				
No	0.29	.005	4925.94	28.04
Yes	0.27	.007	5242.94	52.79
Difference	0.0189 (1.99)		-317.00(-5.82) ***	
CSA practices				
No	0.30	0.005	4965.62	28.72
Yes	0.27	0.007	5193.66	53.71
Difference	.0331(3.40) ***		-228.036(-4.08) ***	

To measure the impact of adoption on the food insecurity indicator and net crop income, we need to take into account the fact that households who adopted the practices might have achieved a higher productivity even if they had not adopted.

We categorize our explanatory variables hypothesized to explain the adoption decision and resulting food security indicators under five major categories: (1) climatic and bio-physical variables, (2) plot level characteristics, (3) institutional variables, (4) household wealth and (5) household demographics.

Given the high variability that Ethiopian farmers have to face, climate variables characterizing the community where the plot is located might be relevant to explain the adoption decisions of the farmers. For input decisions, we use long-term historical data on rainfall patterns and temperatures to capture expected climate at the beginning of the season. For food security indicators, we include actual climate realizations. For input use decision, we use rainfall variation over time as represented by the coefficient of variation of rainfall[9], long-term mean rainfall, the number of decades that the maximum temperature was greater than 30º C, and long-term mean average temperature.

Lower mean rainfall and higher temperatures are expected to increase CSA inputs, whereas higher mean rainfall and lower temperatures should favour improved seeds and fertilizer use. Greater riskiness, reflected in the coefficients of variation, is expected to increase use of CSA inputs, but decrease use of improved seeds and fertilizer. For crop income and the subjective food security indicator, we use growing season rainfall and average temperature observed in the growing season.

From Table 4 we can observe that there are significant differences between the adopter categories in terms of the climatic variables. For instance the adoption of modern inputs with respect to non-adoption is reduced when the coefficient of variation of rainfall increases, when the long-term average temperature is increased, and when the number of decades in the rainy season reporting an average maximum temperature higher than 30 degrees (between 1989-2010) is lower.

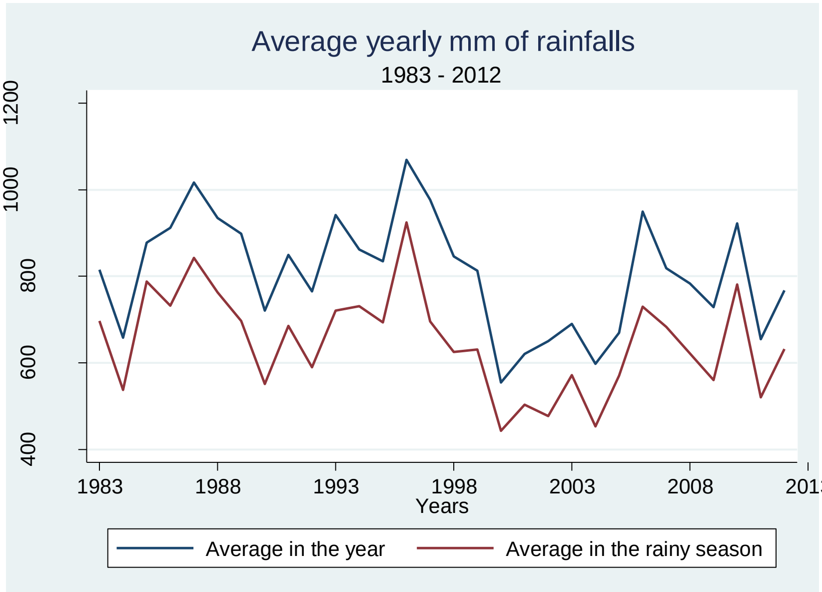
[9] Coefficient of variation is measured as the standard deviation divided by the mean for the respective periods: 1983-2011

Table 4. Summary statistics of climatic variables by adoption decision

	Modern inputs	CSA practices	Mixed practices	None	Mean of all practices	SD of all practices
Average temperature during rainy season	18.56***	20.08	19.18***	19.99	19.57	2.3
	[0.04]	[0.05]	[0.07]	[0.04]		
Rainfall during rainy season (mm)	555.79***	536.06	523.98**	536.84	539.98	167.34
	[3.29]	[3.44]	[4.78]	[2.68]		
Coefficient of variation rainfall (1989-2011)	0.26***	0.28***	0.29***	0.27	0.28	0.06
	[0.00]	[0.00]	[0.00]	[0.00]		
Long-term mean rainfall during rainy season (1989-2011) (mm)	694.25***	656.55**	620.48***	668.40	667.18	224.66
	[4.54]	[4.69]	[6.46]	[3.50]		
Long-term average temperature during rainy season (1989-2011)	18.41***	19.97**	19.05***	19.85	19.44	2.26
	[0.04]	[0.05]	[0.07]	[0.03]		
Rainfall shortfalls (2006-2011)	51.85***	49.55***	49.55***	46.95	48.98	27.35
	[0.57]	[0.58]	[0.84]	[0.41]		
Coefficient of variation of temperature (1989-2010)	0.02***	0.02***	0.02***	0.02	0.02	0.00
	[0.00]	[0.00]	[0.00]	[0.00]		
# dekades in rainy season av. max temp over 30 (1989-2010)	8.04***	15.55**	9.44***	18.13	14.19	40.06
	[0.63]	[0.82]	[0.77]	[0.72]		

Data from NOAA presented in Figure 1 show the time pattern of average rainfalls during the rainy season in Ethiopia. The last thirty years were characterized by a decreasing trend in rainfall and significant fluctuations from one year to another, determining an increase in the risk of climate change in Ethiopia.

Figure 1. Rainfall in rainy season over time (1983-2012)



The diagram in Figure 2 presents the trends over time of average temperature in the year and in the rainy season. Average temperatures in the rainy season are clearly higher than those in the whole year except for 1996 where the two temperatures coincide. If recent warming trends continue, most of Ethiopia will experience more than a 1 Celsius (°C) increase in air temperature, with the warming tendency projected to be greatest in the south-central part of the country. This warming will intensify the impacts of droughts, and could particularly reduce the amount of productive crop land for many crops (FEWS NET, 2011). Thus, more frequent droughts and drier climate generally may be producing repeated shocks that increase vulnerability and activate a cycle of poverty.

Figure 2. Average temperature over time (1989-2010)

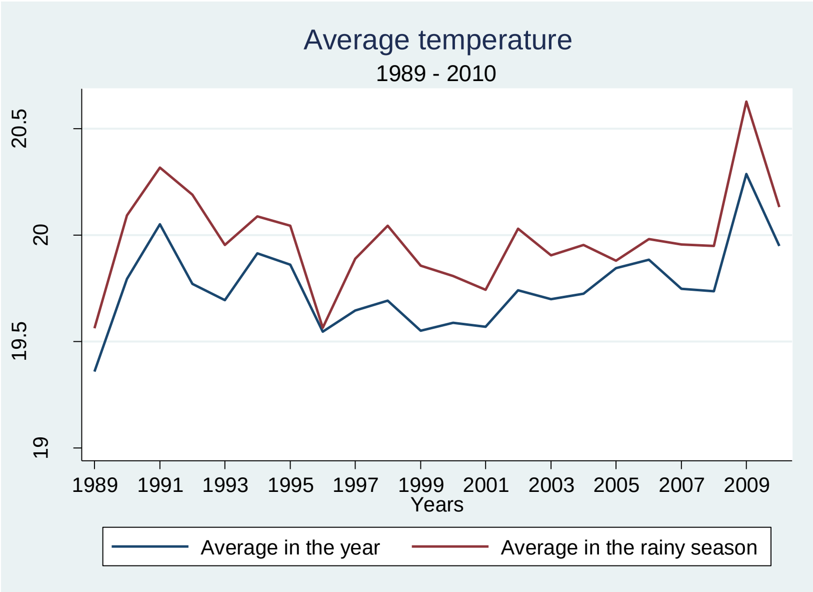


Figure 3 shows the geographic distribution of the coefficient of variation of rainfall and temperature at the EA level. As can be seen, there are significance differences in terms of rainfall and temperature variability across the three geographical regions in major regions of Ethiopia. Figure 4 shows the geographic distributions of current and long run average rainfall and we can observe that the Tigray region experiences relatively low level of rainfall compared to the other regions. As for current and long run average temperature, Figure 5 clearly shows that the areas in the Oromia and SNNP experience low temperatures followed by the Amhara region.

Figure 3. Coefficient of variation of rainfall and max temperature (1983-2011)

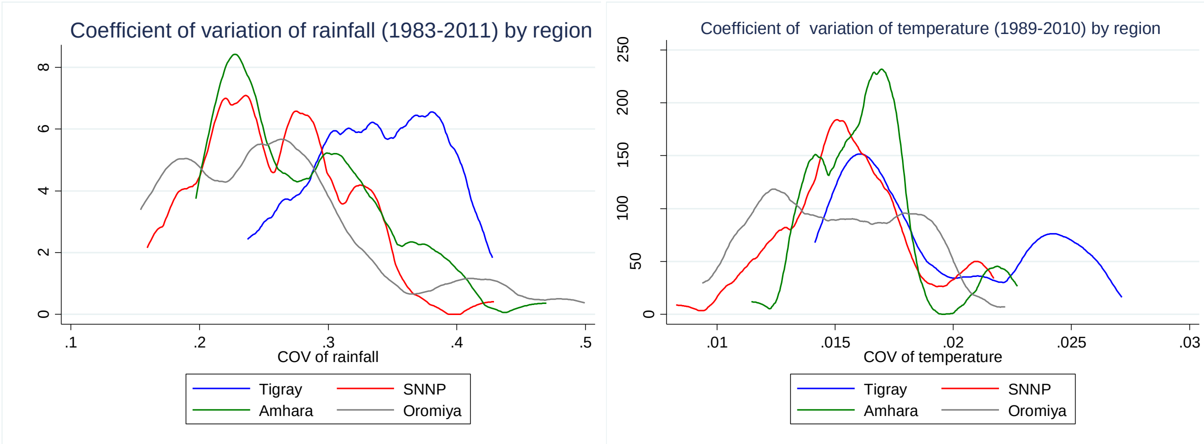


Figure 4. Total amount of rainfall during the rainy season (current and long run)

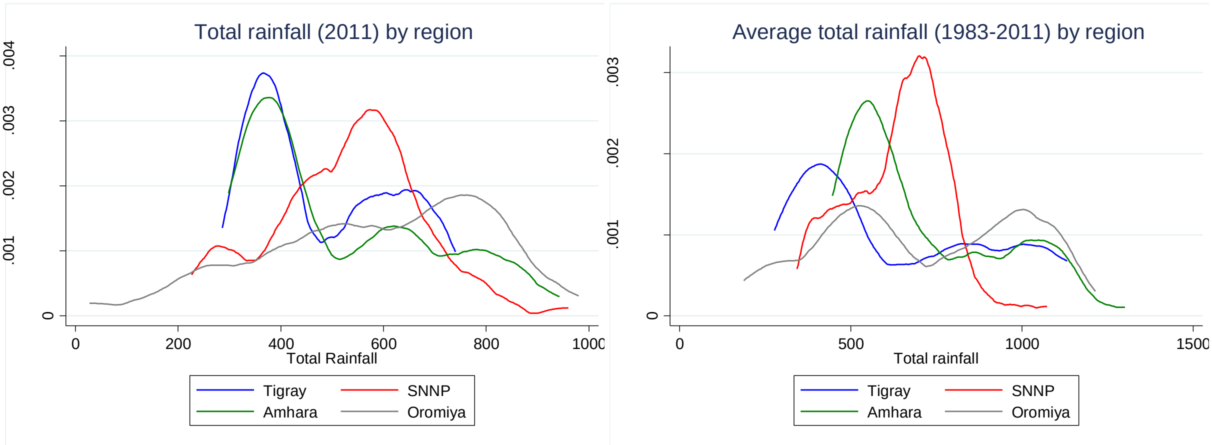


Figure 5. Average temperature during rainy season (current and long run)

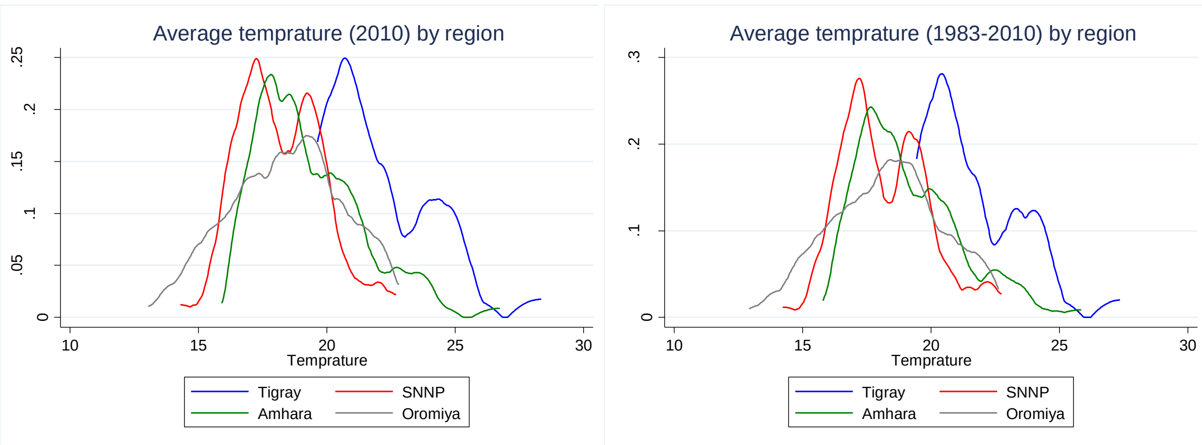


Table 5 shows the holder and household socio-economic characteristics information by adoption decisions, distinguishing between modern inputs (improved seeds or chemical fertilizer), CSA practices (legume intercropping, organic fertilizer or anti-erosion measures) and a mix of them (modern or CSA) versus no adoption. Table 3 illustrates the factors characterizing the adopters of the three categories of practices but simply comparing the averages values does not allow disentangling the causal relationship between these factors and the adoption of different measures.

Table 5. Summary statistics of the variables used in the analysis by adoption decision

	Modern inputs	CSA practices	Mixed practices	None	Mean of all practices	SD of all practices
Dummy for female holder (1=yes)	0.14	0.16***	0.17***	0.13	0.14	0.35
	[0.01]	[0.01]	[0.01]	[0.01]		
Age of the holder	44.39	46.81***	46.04**	44.86	45.29	14.77
	[0.30]	[0.33]	[0.48]	[0.23]		
Squared age of the holder	2176.69	2409.58***	2331.16*	2237.03	2269.48	1466.75
	[29.45]	[32.87]	[48.87]	[23.10]		
Dummy for at least literate HH head (1=yes)	0.36***	0.28	0.33**	0.29	0.31	0.46
	[0.01]	[0.01]	[0.01]	[0.01]		
Sex ratio in the HH (f/m)	1.15	1.14	1.19	1.16	1.15	0.91
	[0.02]	[0.02]	[0.03]	[0.01]		
Dependency ratio in the HH	1.18	1.22	1.31***	1.2	1.21	0.93
	[0.02]	[0.02]	[0.03]	[0.01]		
Household size	5.71***	5.65***	5.69***	5.48	5.59	2.21
	[0.05]	[0.05]	[0.07]	[0.03]		
Log area of field (hectares)	0.21***	0.12***	0.15***	0.17	0.17	0.2
	[0.00]	[0.00]	[0.01]	[0.00]		
Land tenure (owner) (1=yes)	0.76	0.90***	0.88***	0.77	0.81	0.39
	[0.01]	[0.01]	[0.01]	[0.01]		
Log of wealth index	-0.08***	-0.14	-0.07***	-0.14	-0.12	0.32
	[0.01]	[0.01]	[0.01]	[0.00]		
Log of agriculture wealth index	0.08***	-0.04	0.03***	-0.06	-0.01	0.56
	[0.01]	[0.01]	[0.02]	[0.01]		
Log of number of oxen (in TLU)	0.54***	0.42	0.44	0.42	0.45	0.34
	[0.01]	[0.01]	[0.01]	[0.01]		
Dummy for getting credit services (1=yes)	0.46***	0.23	0.41***	0.22	0.3	0.46
	[0.01]	[0.01]	[0.02]	[0.01]		
Dummy for getting advisory services (1=yes)	0.85***	0.63	0.80***	0.62	0.7	0.46
	[0.01]	[0.01]	[0.01]	[0.01]		
Log of Elevation (meters)	2.28***	2.38***	2.31***	2.35	2.33	0.35
	[0.01]	[0.01]	[0.01]	[0.01]		

Log of Potential Wetness Index	2.61***	2.56	2.61***	2.57	2.58	0.15
	[0.00]	[0.00]	[0.00]	[0.00]		
Log of Nutrient availability (scale 1-5, with 1= no constraint and 5= non-soil)	0.79***	0.80***	0.77***	0.88	0.83	0.21
	[0.00]	[0.00]	[0.00]	[0.00]		
Workability (constraining field management) (scale 1-5, with 1= no constraint and 5= non-soil)	2.70***	2.91	2.63***	2.93	2.84	1.20
	[0.02]	[0.03]	[0.04]	[0.02]		
Dummy of large weekly market in the community (1=yes)	0.45	0.45	0.37***	0.43	0.43	0.5
	[0.01]	[0.01]	[0.01]	[0.01]		
Dummy of collective action for Natural Resource Conservation (soil, water, afforestation) (1=yes)	0.61***	0.60***	0.59***	0.5	0.56	0.5
	[0.01]	[0.01]	[0.02]	[0.01]		
Regions						
Tigray	0.16***	0.13***	0.26***	0.07	0.13	0.33
	[0.01]	[0.01]	[0.01]	[0.00]		
Amhara	0.22***	0.30***	0.23***	0.27	0.26	0.44
	[0.01]	[0.01]	[0.01]	[0.01]		
Somalie	0.00***	0.04***	0.00***	0.06	0.03	0.18
	[0.00]	[0.00]	[0.00]	[0.00]		
Benshagul Gumuz	0.02***	0.02***	0.01***	0.04	0.03	0.16
	[0.00]	[0.00]	[0.00]	[0.00]		
SNNP	0.28***	0.16***	0.21	0.21	0.22	0.41
	[0.01]	[0.01]	[0.01]	[0.01]		
Harari	0.02	0.06***	0.14***	0.02	0.04	0.2
	[0.00]	[0.01]	[0.01]	[0.00]		
Diredwa	0.01***	0.09	0.01***	0.09	0.06	0.23
	[0.00]	[0.01]	[0.00]	[0.00]		

The average age of the sample household is about 45 years old and only about 14 percent are headed by females. The average household size is about 5.5 while the sex and dependency ratios are about 1.15 and 1.21 respectively. About 30 percent of household heads can read and write. Household wealth indicators include a wealth index[10] based on

[10] The household wealth index is constructed using principal component analysis, which uses assets and other ownerships. In this specific case the following variables have been included: a set of dummy variables accounting for the quality of dwelling such as wall, roof and floor, a set of dummy variables capturing the ownership of kitchen, oven, toilet, bathing facilities, waste disposal

durable goods ownership and housing condition, and livestock size (measured in tropical livestock unit (tlu)). Family size in terms of adult equivalent units is a potential indicator of labour supply for production, and labour bottlenecks can also be a significant constraint to the use of some farm management practices. For instance, investments in anti-erosion measures can be particularly labour demanding and may be too expensive to undertake in households with limited access to labour. We expect that farmers who are wealthier or have higher number of livestock may be more flexible in experimenting with new technologies and may use their animals for traction and transportation, facilitating access to credit and productivity.

We also consider several plot-specific characteristics, such as land tenure structure, plot size and soil quality of the plot. Better tenure security increases the likelihood that farmers adopt strategies that will capture the returns from their investments in the long run (e.g. Kassie and Holden, 2008; Denning et al., 2009; Teklewold et al., 2013). The use of modern inputs is more frequent in larger plots. Moreover, new technologies are generally embraced in plots where the soil quality is good in terms of elevation, wetness and nutrient availability.

Indicators for institutions include the access to credit service, access to extension programs, distance to nearest population centres and collective action. By increasing travel time and transport costs, distance related variables are expected to have a negative influence on adoption decisions. By facilitating information flow or mitigating transactions costs, access to institutions variables are expected to have a positive effect on the adoption decision.

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facilities, drinking water, kerosene/electric/gas stove, blanket/gabi, bed, table, chair, fan, radio, tape/CD player, TV/VCR, sewing machine, paraffin/ refrigerator, bicycle, car/motorcycle/minibus/lorry, beer brewing drum, sofa, coffee table, cupboard, lantern, clock, iron, computer, fixed phone line, cell phone, satellite dish, air-conditioner, washing machine, generator, solar panel, and desk. The agriculture household wealth index is constructed using principal component analysis only on agricultural assets and ownership such as cart (hand pushed), cart (animal drawn), water storage pit, mofer and kember, sickle (machid), axe (gejera), pick axe (geso), traditional and modern plough and water pump.

4. Empirical strategy

4.1 Modelling adoption decisions

The adoption decisions of smallholder farmers in Ethiopia can be modelled as optimization processes where rational and heterogeneous agents maximize their expected utility functions subject to budget, information and credit access constraints and the availability of both the technology and other inputs (de Janvry et al., 2010). Assuming that adoption is actually a choice that can be taken (no constraints are considered), the adoption decision of a risk-averse farmer *i*, (A_i), depends on a set of variables observable by the researcher (Z_i), a set of variables that are unobservable (U_i) and an i.i.d. error term (ε_i)

$$A_i = \begin{cases} 1 \; if \; E\pi(Z_i, U_i;\; A_i = 1) - E\pi(Z_i, U_i;\; A_i = 0) + \varepsilon_i > 0 \\ 0 \qquad\qquad\qquad\qquad\qquad\qquad otherwise \end{cases} \qquad (1)$$

The farmer will choose to adopt if the expected profit function achieved from adopting is greater than the expected profit function of not adopting (de Janvry et al., 2010). In an endogenous risk framework, adoption strategies may affect the probability of a bad nature state occurring by, for example, modifying the likelihood of extreme climate events (mitigation) and consequently reducing the severity of damage on crop production (adaptation). If the effect of climate change can be parameterized by the continuous, non-negative random variable $\gamma \in \Gamma = [0, \overline{\gamma}]$, with a probability distribution $\gamma \sim \mathrm{F}(\gamma; \mathrm{A_i}) \colon \Gamma \to [0,1]$ and where higher γ means a more aggressive climate event and $\gamma = 0$ means low climate variability or no extreme weather event, the farmer's expected profit function can be written as:

$$\begin{cases} \mathrm{E\pi(Z_i, U_i;\; A_i = 1) = Y_i - C(A_i)} - \int_0^{\overline{\gamma}} \mathrm{L(\gamma)dF(\gamma; A_i)} \\ \qquad \mathrm{E\pi(Z_i, U_i;\; A_i = 0) = Y_i} - \int_0^{\overline{\gamma}} \mathrm{L(\gamma)dF(\gamma; 0)} \end{cases} \qquad (2)$$

where $\mathrm{Y_i}$ is the outcome variable (for example, net crop income, household consumption or food security status), $\mathrm{C(A_i)}$ is the cost function of adoption, $\mathrm{L(\gamma)}$ is the money equivalent of realized damage and the integral is the Stieltjes integral (Sproul and Zilberman, 2011). The outcome variable $\mathrm{Y_i}$ is a function of observed variables (X_i), unobserved variables (V_i), adoption status (A_i) and an i.i.d. error term η_i:

$$\mathrm{Y_i} = \mathrm{Y_i}(X_i, V_i, A_i(Z_i, U_i, \varepsilon_i), \eta_i) \qquad (3)$$

It is however important to note that farmers are more likely to adopt a mix of measures to deal with a multitude of agricultural production constraints than to adopting a single practice. In this context, recent empirical studies showed that the existing inter-relationships between the various technologies may mislead the influence of various factors on the adoption decisions and that interdependent and simultaneous adoption decisions can be captured only in a multiple technology choice framework (Wu and Babcock, 1998; Dorfman, 1996; Teklewold et al., 2013). We, thus, use a multivariate probit model (MVP) technique applied to multiple plot observations, which treats the five equations of adoption as independent from each other except for modelling their underlying errors as jointly normally distributed. The adoption equations of the *k-th* agricultural strategy with $k = 1,2,3,4,5,$ on plot *m* by the *i-th* farm/household can be written as

$$A_{im}^k = \alpha Z_{im} + \beta U_i^k + \varepsilon_{im} \qquad (4)$$

where A_{im}^k is a latent variable which is supposed to be a linear combination of observed characteristics, Z_{im} are household, plot, climatic and community characteristics that affect the adoption of the *k-th* practice, U_i^k are unobserved characteristics and ε_{im} is the error term. The correlation between ε_{im} over the different adoption decisions can be positive, and in this case the agricultural strategies are complementary or negative when the practices are substitutive. When the adoption of a practice is independent from the adoption of other agricultural strategies, then equation (4) is not a system of five equations but becomes five different equations specifying univariate probit models. As showed from Table 2, about 20 percent of the plots are treated with more than one practice, and so we choose a specification that allows the error terms to jointly follow a multivariate normal (MVN) distribution, with zero conditional mean and variance normalized to unity. Thus, in the covariance matrix the off-diagonal elements represent the unobserved correlation between the stochastic components of the *k-th* farming practices.

4.2 Modelling impact of adoption

As the adoption of agricultural practices is potentially endogenous, e.g. the unobservable variables $\mathrm{V_i}$ and $\mathrm{U_i}$ can be correlated, the estimation of the impact of adoption decision on the outcome variable, equation (3), might generate biased estimates if not properly dealt with (de Janvry et al., 2010).

There is a problem of selection bias because farmers endogenously self-select themselves. Unobservable characteristics such as farmer ability, for example, which is not entirely captured by education and age, may affect crop production but also improves the returns of technology and consequently increases the probability of adoption. As noted by Foster and Rosenzweig (2003), other factors such as soil quality or rainfall shocks might affect returns and the decision to adopt simultaneously and if not observed may produce endogeneity problems. The wide availably of climate and bio-physical data in our dataset allows us to control for soil quality, rainfall and temperature phenomena. However, other unobservable characteristics (farmer ability, expectation of yield gain from adoption and motivation) may influence decisions of adoption and meanwhile be correlated with the outcomes of interest. This requires a selection correction estimation method.

To explicitly account for multiple endogeneity problems in our structural model, we employ a conditional recursive mixed-process estimator (CMP) as proposed by Roodman (2011) which is suitable for dealing with many simultaneous equation models, in which endogenous variables appear on the right side of structural equations. The advantage with this approach, as opposed to two-stage least squares and related linear methods, is the gain in efficiency, as it takes into account the covariance of the errors and uses the information about the limited nature of the reduced-form dependent variable (Roodman, 2011). Moreover, despite the usual methods of instrumental variables, the number of instruments can be different from the number of endogenous variables. The major limitation of implementing this approach is the feasibility in terms of computational burden and achieving convergence especially for a large family of multi-equations. For our case, we cannot achieve convergence when implementing all the six equations simultaneously; therefore, we restricted ourselves to a maximum of three equations at a time for this paper.

Looking at the MVP results, we categorized the five adoption variables into two groups based on similarities in terms of factors affecting them and nature of the technologies - modern inputs (improved seed or chemical fertilizer) (A_{im}^1) and CSA (use of organic fertilizer or legume intercropping or anti-erosion measures) (A_{im}^2).

$$Y_{im} = \omega X_{im} + A_{im}^{k} + \eta_{im} \quad (5)$$
$$A_{im}^{k} = \alpha Z_{im} + \varphi I_{i}^{k} + \varepsilon_{im} \ \ with\ k = 1,2 \quad (6)$$

where Y_{im} is the outcome variable (crop net income and the subjective food insecurity indicator), X_{im} is the matrix of exogenous variables affecting the outcome variable, and $\mathrm{A}_{\mathrm{i}}^{\mathrm{k}}$ are the variables of adoption as defined above. In the adoption equations (6), Z_{im} is the matrix of exogenous variables affecting adoption decisions, I_{i}^{k} is the matrix of instruments for the correction of endogeneity and η_{im} is the error associated with the impact model.

When the outcome variable, Y_{im} , of equation (5) is a continuous and nonnegative skewed outcome variable such as the annual net income from crop activities[11], we need to consider using a different model. There are many models, zero-inflated or not, for nonnegative outcomes, but few have the robustness of Poisson (Nichols, 2010). We prefer to use the Poisson model instead of OLS on logarithm of income, firstly because it permits to handle outcomes that are zero. Secondly, small nonzero values, however they arise, can be influential in log-linear regressions. Poisson regression understands that values such as 0.01, 0.0001, 0.0000001, and 0 are indeed nearly equal. Even when we have no reason to assume that the variance of the log of income is equal to its mean, as the Poisson process requires, we can fit our model by using Poisson regression rather than linear regression. It derives that the estimated coefficients of the maximum-likelihood Poisson estimator in no way depend on the assumption that the mean is equal to the variance, so that even if the assumption is violated, the estimates of the coefficients are unaffected. In the maximum-likelihood estimator for Poisson, what does depend on the above assumption are the estimated standard errors of the coefficients. If the assumption of the mean equal to the variance is violated, the reported standard errors are useless. Thus, we specify that the variance-covariance matrix of the estimates (of which the standard errors are the square root of the diagonal) be estimated using the Huber/White/Sandwich linearized estimator.

4.3 Exclusion restriction

The consistency of this method depends on the validity of instruments (I_i), which in turn, relies on two conditions. First, the instruments must be correlated with the endogenous variables (adoption of agricultural practices). Second, they must not be correlated with the unobserved factors that may affect the crop net income or food insecurity status of the household (i.e. η_{im}). We consider using coefficient of variation of rainfall (CoV) (1983-2011), average shortfall of rainfall (2006-2011) [12], coefficient of variation of temperature (1983-2011) and long-term average rainfall (1983-2011) as potential instruments for the

[11] Annual net income from crop activities can be also negative and thus we transform the variable by adding the absolute value of its minimum value.

[12] Shortfall variable have been computed as the average distance between the yearly precipitations during rainy season and their long-term mean. For those years reporting a level of rainfall higher than the long-run average the distance has been considered zero.

household decision to adopt agricultural practices during the current year. If farmers form expectations about the climatic conditions of their area, we might expect that they plant crops and use farm practices that are suited to their expectations. The formation of these expectations is key for production. Thus for households in rural areas, climate variation across space and time should generate corresponding variation in household response or behaviour in terms of change in farm practices that will in turn create variation in agricultural output and thus household income. Its impact on expected utility maximization is realized mainly through input choices. For this reason, we focus on climate variability which, we argue, generates uncertainty about expected climatic conditions.

We are quick to point out the selected instrumental variables may not be perfect and to address a potential weak instrument and under identification problems, we also implement instrumental variables estimation using heteroskedasticity-based instruments with the new user written command ivreg2h by Baum and Schaffer (2012). Exploiting heteroskedasticity, ivreg2h estimates an instrumental variables regression model, providing the option to generate instruments using Lewbels (2012) method.

5. Estimation results and discussion

5.1 Determinants of the adoption decision

Our first objective in this study is to examine how different factors influence household adaptation strategies at the plot level and secondly we try to evaluate the causal impact of the farmer adoption decision on crop net income and the subjective food insecurity indicator. Concerning the first objective, the maximum likelihood estimates of the MVP model of adoption of farm management practices are presented in Table 7. It provides the driving forces behind farmers' decisions to adopt farm management strategies where the dependent variable takes the value of 1 if the farmer adopts specific practices on a given plot and 0 otherwise. The model fits the data reasonably well – the Wald test of the hypothesis that all regression coefficients in each equation are jointly equal to zero is rejected. Also the likelihood ratio test of the null hypothesis that the error terms across equations are not correlated is also rejected $(\chi^2(171) = 6{,}755.92,\ P = 0.00)$ as reported in Table 6.

From the estimated correlation coefficients of error terms reported in Table 6, we can also highlight the complementarities and the substitutability between the practices. We find that the estimated correlation coefficients are statistically significantly different from zero in eight of the ten pair cases, where three coefficients are negative and the remaining five are positive, suggesting that the propensity of adopting a practice is conditioned by whether another practice in the subset has been adopted or not (see Table 6). Besides justifying the use of MVP in comparison to the restrictive single equation approach, the sign of the coefficients support the notion of interdependency between the adoption decision of different farm management practices, which may be attributed to complementarity or substitutability between the practices which is consistent with the findings of Teklewold et al. (2012). We find that the use of chemical fertilizer is complementary to the use of improved seed but substitutable with legume intercropping and organic fertilizer. The positive correlation coefficient between two yield enhancing technologies (chemical fertilizer and improved seed) is the highest among all (30.7%) which is not surprising given the fact that the productivity potential of high yielding varieties highly depends on the use of chemical fertilizer. This is one of the reasons why poor farmers may refrain from switching to high yielding varieties if they do not have capital to purchase chemical fertilizer afterwards. The substitutability between organic and chemical fertilizer is consistent with the findings of Teklewold et al. (2012) although it contradicts the result found by Marenya and Barrett (2009). On the other hand improved seed is significantly complementary with the use of organic fertilizer and anti-erosion measures. Adoption of organic fertilizer is also significantly complementary with maize-legume intercropping. The positive correlation between adoption of maize-legume intercropping and use of organic fertilizer indicates that, given the very low soil fertility of most farmland in Ethiopia currently, low cost fertility-improving inputs are still complements and not yet substitutes.

Table 6. Estimated covariance matrix of the regression equations between the adaptation measures using the MVP joint estimation model

	Improved seeds	Legume intercropping	Organic fertilizer	Anti-erosion measures
Chemical fertilizer	0.307(0.036)***	-0.176(0.046)***	-0.136(0.025)***	0.270(0.044) ***
Improved seeds		0.091(0.058)	0.100(0.033)***	0.247(0.054) ***
Legume intercropping			0.188(0.034)***	-0.145(0.083) *
Organic fertilizer				-0.024(0.042)

Likelihood ratio test of rho21 = rho31 = rho41 = rho51 = rho32 = rho42 = rho52 = rho43 = rho53 = rho54: chi2(10) = 6755.92 Prob > chi2 = 0.0000

Standard errors in parenthesis

Note: *** p<0.01, ** p<0.05, * p<0.1

Results also show the importance of climatic variables characterizing the community where the plot is located in explaining the probability of farm households' decision to adopt different agricultural practices. We use long-term historical data on rainfall patterns and temperatures such as coefficient of variation of rainfall, long-term rainfall and temperature and number of decades that the maximum temperature was greater than 30º C to capture expected climate at the beginning of the season. Greater riskiness, reflected in the coefficients of variation, is expected to increase use of risk reducing inputs such as CSA practices, but decrease use of improved seeds and fertilizer. Lower mean rainfall and higher maximum temperatures are expected to increase CSA inputs, whereas higher mean rainfall and lower maximum temperatures should favour improved seeds and fertilizer use.

Consistent with this hypothesis, we find that greater variability in rainfall as represented by the coefficient of variation of rainfall variable increase adoption of risk-reducing practices but reduce the use of inputs with uncertain benefits in terms of reducing risk to current climate stresses. For instance, in regions with greater variability in rainfall, more legume intercropping and anti-erosion measures are used, whereas the probability of adopting chemical fertilizer is low in areas where the rainfall variability is high. The only one exception is improved seed which is positively associated with greater variability. This result corroborates the finding that farmers avoid risk by using CSA inputs and reducing the adoption of expensive inputs.

We also find that communities with higher long term mean rainfall tend to use more improved seed and organic fertilizer, but fewer anti-erosion measures. Higher temperatures also seem to favour legume intercropping and anti-erosion measures but decrease the use of chemical fertilizer and improved seeds. The potential wetness index variable is also significant for chemical fertilizer and improved seeds but negative for legume-intercropping, which is consistent with the findings of findings of Kassie et al. (2010) and Teklewold et al. (2013) who found that yield enhancing technologies like chemical fertilizer provide a higher crop return in wetter areas than in drier areas. Overall our findings suggest that farmers are adopting some practices in response to climate pattern and that climatic variability should be an integral part of promotion activities.

Even if higher climate risk does generate a higher incentive to adopt, results also confirm the importance of other conventional barriers to adoption that need to be addressed. Plot characteristics are found to be important determinants and conditioning factors of adoption for most of the practices. Nutrient retention capacity as defined by the capacity of the soil to retain added nutrients against losses caused by leaching is of particular importance for the effectiveness of fertilizer applications. Farm households with high nutrient availability constraints are less likely to implement farm management practices such as chemical and organic fertilizer. However farm households with less fertile soil or high nutrient availability constraints are more likely to implement anti-erosion measures. We also find that larger plots are more likely to adopt chemical fertilizer and improved seed whereas households with small plots tend to adopt legume inter cropping and organic fertilizer. Moreover, consistent with Kassie et al. (2010) farmers are more likely to use chemical fertilizer and improved seed on rented plots than on their own plots. To the extent that ownership is associated with greater tenure security than rental agreements, particularly in the longer term, better tenure security increases the likelihood that farmer adopt strategies that will capture the returns from their investments in the long run which is consistent with other findings (see Kassie and Holden, 2008; Deininger et al., 2009; Teklewold et al., 2013). As expected, the household wealth indicators such as livestock holding and the wealth index have a positive impact on use of modern inputs.

Results also show the key role of rural institutions and community characteristics in governing the adoption decisions of households. Access to credit and extension services in the community is positively correlated with the use of chemical fertilizer and improved seed but in communities where availability of credit service is limited, farmers tend to use more of CSA measures. Distance to nearest population centers, as expected, negatively affects the adoption decision for all inputs; the distance constitutes indeed a constraint on the time that farmers can devote to accessing information and inputs, which in turns determines the cost of production. Households residing in communities with large populations tend to adopt more CSA inputs. Collective action affects positively the adoption of legume intercropping but there is no statistical significant relationship for other input use.

Household demographics do not seem to play a significant role in explaining the household adoption decision. One interesting finding is that the propensity of adopting chemical fertilizer, legume intercropping and organic fertilizer is higher for female plot holders, confirming the crucial role of women in Ethiopian agriculture (see Table 7 for details).

To summarize, what emerges clearly from the multivariate probit regression is that factors influencing the adoption choice are diverse according to the practice considered, confirming Knowler & Bradshaw (2007). On the one hand, yield enhancing inputs such as chemical fertilizer are adopted in communities with lower climate variability and lower temperatures. Since the adoption of yield enhancing inputs requires skills and access to capital, inputs such as chemical fertilizer and improved seed are used mainly by wealthier households and/or households having access to credit and extension services. On the other hand, the use of risk reducing inputs such as CSA practices is adopted in regions with higher climate variability and higher temperatures. Besides, this practice is adopted conditioned to stable land tenure and is accessible also to households with lower level of wealth and limited access to credit.

Table 7. MVP estimates of barrier to adoption

	Chemical fertilizer		Improved seeds		Legume inter-cropping		Organic fertilizer		Anti-erosion measures	
	coef	se	coef	se	coef	se	coef	se	coef	se
Climatic variables										
Coefficient of variation of rainfall	-3.183***	0.789	2.122*	1.132	0.878	0.927	3.185***	0.660	2.656*	1.542
Long-term mean rainfall	-0.000	0.000	0.001*	0.000	-0.000	0.000	0.001***	0.000	-0.002***	0.000
Long-term average temperature	-0.172***	0.020	-0.129***	0.029	0.235***	0.026	0.012	0.017	0.089**	0.045
# dekades av. max temp over 30 (1989-2010)	-0.002	0.001	0.004**	0.002	0.016***	0.003	0.000	0.001	0.002	0.002
Potential Wetness Index	0.068***	0.016	0.066***	0.019	-0.033*	0.019	0.006	0.014	0.024	0.033
Plot and bio-physical characteristics										
Log (land size in hectares)	0.449***	0.147	0.012	0.153	-0.492**	0.224	-0.917***	0.165	-0.855***	0.264
Land tenure (1=owner)	-0.126**	0.061	-0.032	0.071	0.183**	0.088	0.618***	0.062	0.122	0.119
Nutrient availability	-0.328***	0.082	0.040	0.072	-0.108*	0.061	-0.148***	0.048	0.356***	0.096
Terrain Roughness	-0.028***	0.011	-0.023	0.016	-0.007	0.012	0.014*	0.009	-0.017	0.023
Workability (constraining field management)	0.072**	0.031	-0.191***	0.043	0.065*	0.037	-0.038	0.025	-0.244***	0.065
Household wealth variables										
Wealth index	0.081***	0.021	0.053**	0.026	-0.035	0.058	-0.001	0.030	0.045	0.034
Number of oxen	0.174***	0.052	0.157*	0.080	0.045	0.060	0.038	0.041	-0.421***	0.123
Institutional variables (EA level)										
Access to credit services (1=yes)	0.374***	0.067	0.034	0.072	-0.210**	0.096	-0.092*	0.052	-0.306**	0.124
Log (number of population of the community)	0.005	0.055	0.109	0.071	0.195***	0.069	0.253***	0.049	0.572***	0.139
Access to extension program (1=yes)	1.692***	0.076	1.473***	0.082	-0.161	0.116	-0.041	0.061	-0.097	0.105
Log (distance in to nearest population centre) (km)	-0.270***	0.049	-0.097*	0.053	-0.161***	0.054	-0.054	0.041	-0.436***	0.079

Collective action for natural resource conservation (1=yes)	-0.018	0.062	0.070	0.070	0.160**	0.070	0.070	0.051	-0.077	0.127
Socio demographic variables										
Dummy for female holder	0.150*	0.088	0.126	0.112	0.212**	0.101	0.204***	0.072	-0.040	0.164
Log (age of the holder)	4.344	14.804	2.380	19.919	10.532	14.052	-30.536*	17.429	-2.255	40.062
Log (age squared of the holder)	-2.178	7.218	-1.174	9.715	-5.226	6.849	14.962*	8.511	1.338	19.574
Education of the head (1=literate)	0.045	0.068	-0.042	0.081	-0.062	0.081	0.062	0.054	-0.038	0.142
Sex ratio (f/m)	0.029	0.028	0.049	0.037	-0.021	0.033	-0.015	0.024	0.096	0.063
Dependency ratio	-0.027	0.033	0.093*	0.049	0.042	0.038	0.070**	0.029	-0.102	0.074
Log (household size)	0.004	0.097	-0.056	0.131	-0.011	0.122	-0.011	0.087	0.151	0.199
Regions (reference: Oromia)										
Tigray	0.529***	0.162	-0.840***	0.221	-1.290***	0.298	-0.066	0.117	2.093***	0.336
Amhara	-0.336***	0.092	-0.300***	0.113	-0.173	0.113	-0.030	0.069	1.657***	0.295
Somalie	-1.251***	0.405	0.073	0.211	-0.171	0.260	-0.128	0.207	-0.000	0.375
Benshagul Gumuz	-0.055	0.206	0.208	0.220	0.283	0.296	0.120	0.199	-0.000	0.459
SNNP	0.209***	0.080	0.117	0.127	0.393***	0.108	-0.193**	0.080	0.471*	0.276
Harari	0.622***	0.168	-0.185	0.218	0.194	0.167	0.522***	0.153	-0.000	0.288
Diredwa	-1.128***	0.256	0.722***	0.196	-0.193	0.179	-0.389**	0.156	-0.000	0.349
Constant	3.609*	1.984	-1.513	2.520	-7.767***	1.996	-1.406	2.105	-3.825	4.783
Number of observations						8,219				
Log Likelihood						-11,795.50				
Prob > chi2						0.0000				

note: *** p<0.01, ** p<0.05, * p<0.1

5.2 Impact on crop income and food insecurity

Table 8 reports Poisson[13]/Probit, conditional recursive mixed-process estimator (CMP) results and instrumental variables estimation using heteroskedasticity-based instruments (with additional instruments constructed using Lewbel, 2012 method) for net crop income and food insecurity[14] equations (all estimates are reported accounting for cluster heteroskedasticity at the household level)[15]. The simplest approach to investigate the effect of adoption consists of estimating Poisson/Probit models of crop net income/food insecurity estimate without controlling for any potential endogeneity problems and with a dummy variable equal to 1 if the farmer decided to adopt the practices on a given plot, 0 otherwise (as in column 1 and 4 of Table 8). The Poisson results (column 4) obtained without controlling for any potential endogeneity problems lead us to conclude that the adoption of agricultural strategies does affect the crop net income whereas the Probit results (column 1) lead us to conclude that the adoption of agricultural strategies does not affect the probability of being in a food insecurity condition. However, these approaches assume that the adoptions of these agricultural practices are exogenously determined while, as previously illustrated, they are potentially endogenous. Therefore the estimation through Poisson/Probit would yield biased and inconsistent estimates.

To measure the impact of adoption, it is necessary to take into account the fact that households who adopted the practices might have achieved a higher productivity even if they had not adopted the practices. For this reason, when we estimate the structural model we need to take into account the endogeneity inherent in the adoption strategies. The impact estimates presented further on use the conditional recursive mixed process (CMP) technique to account for this problem and instrumental variables techniques boosted by the Lewbel (2012) method (ivreg2h) to correct for weak instruments and heteroskedasticity problems.

Before proceeding on with the CMP/IV estimation, we need to test the validity of the instruments chosen. As elaborated in the previous section, we use coefficient of variation of rainfall, average rainfall shortfalls, long-term average rainfall and coefficient of variation of temperature as instruments for the household decision to adopt agricultural practices

[13] The distribution of net crop income is very similar to a Poisson distribution and for the reasons explained in Section 4, we adopted the Poisson model instead of OLS on logarithm of income.

[14] Here the subjective food insecurity indicator is defined as 1 if the household, in the last 12 months, faced a situation where not enough food to feed the household was available and 0 otherwise.

[15] As discussed in the previous section the CMP approach has a caveat in terms of computational burden and achieving convergence for a large family of multi-equations. As a result we are not successful in achieving convergence when instrumenting for five of the endogenous variables simultaneously and therefore we restricted ourselves to instrumenting two endogenous variables at a time. We, therefore, re-grouped the five agricultural practices into two types of strategies: modern inputs, which include chemical fertilizers and improved seeds, and SLM practices, which include legume intercropping, organic fertilizers and anti-erosion measures

during the current year. Valid instruments typically have to satisfy two conditions: they have to be uncorrelated with the error term, which needs a strong theoretical argument and in general cannot be tested, and they have to be highly correlated with the endogenous regressors even after controlling for the exogenous regressors. Empirical and theoretical evidence suggests that IV estimation with weak instruments may perform worse than OLS (surveyed in Stock et al., 2002). In order to test the validity of instruments we performed an instrumental variables estimation using heteroskedasticity-based instruments (the command used in Stata is ivreg2h), which provides the option to generate instruments using Lewbel's (2012) method. This approach may be applied when no external instruments are available, or, alternatively, used to supplement external instruments to improve the efficiency of the IV estimator.

The exogeneity of instruments cannot be tested but when the number of instruments is larger than the number of endogenous variables, the so-called *J-test* for overidentifying restrictions can be computed. The relevance of the instruments can also be tested in the first-stage regression by the *F*-statistic of a joint test of whether all excluded instruments are significant. The test results show that over identification tests support the choice of the instruments, as do the F-test values for all of the specifications. The F-statistic of joint significance of the excluded instruments is greater than 10, thus passing the test for weak instruments. The null hypothesis in the case of the over identification test is that the selection instruments are not correlated with the yield error term and we fail to reject the null in all of the cases.

We can observe that results obtained by the CMP/IV estimator partially differ from the Poisson/Probit ones mainly in the significance of coefficients which suggest the importance of controlling for multiple endogeneity problems simultaneously using the CMP/IV technique. After controlling for the endogeneity problem, both the CMP and IV analysis reveal that adoption of both modern and CSA inputs affect positively the crop net income, although the coefficient for modern input is not statistically significant in the case of the CMP estimator. However the impact of modern and CSA inputs on food insecurity despite having a negative sign which implies reducing food insecurity is not statistically significant, indicating that the adoption of modern or CSA inputs alone doesn’t automatically imply solving food security issues. Our results are partially consistent with earlier studies which state that the use of yield enhancing and CSA inputs is often associated with higher productivity and income (e.g., Mendola, 2007; Teklewold et al 2013; Kassie et al. 2010; Asfaw et al., 2012b, 2012c; Amare et al., 2011 etc).

Household demographic structure also seems explain the variation in crop net income and food insecurity status of the households. Crop net income and food security is significantly higher for households with a literate household head, a smaller family size, a higher sex ratio and a lower dependency ratio. Results also show that crop income and food security is higher for men than women and that this result is robust across the different estimation technique. Our findings are consistent with many studies that show that productivity and income on plots managed by women are lower than those managed by men which is often attributed to difference in input use, such as improved seeds, fertilizers and tools, or other factors such as access to extension services and education (e.g., Quisumbing et al., 2001; Peterman et al., 2011).

We also find a positive relationship between plot size and crop net income and food security (though the coefficient is not significant for crop net income) which is consistent with many other findings in the literature. Tenure status does not have a direct influence on both crop net income and food security controlling for adoption (while it has an indirect effect through the adoption of CSA and modern inputs as discussed in the previous section). Biophysical characteristics of the soil such as nutrient availability constraint, terrain roughness, workability of the soil also has a significant effect on both crop net income and food security although the effect is heterogeneous (in terms of sign and magnitude). As expected, household wealth proxied by a wealth index and number of oxen ownership is also positively and significantly correlated with crop net income and food security of households. Access to credit on the other hand is positively correlated only with crop net income.

Climatic variables play a significant role in explaining variation in crop net income and the food security indicator. Average precipitation and temperature during the rainy season is positively and significantly associated with food security and crop net income. Results also show a large geographical variation in crop income and food security as captured by significant and heterogeneous (in terms of sign and magnitude) coefficients of the region dummies.

Table 8. Impact of adoption on food insecurity indicator and net crop income per capita

	Subjective food insecurity indicator (1=yes)						Net crop income (Birr/capita)					
	PROBIT		IV		CMP		POISSON		IVPOISSON		CMP	
	coef	se	coef	se	coef	se	coef	se	coef	se	coef	se
Modern inputs (1=yes)	0.060	0.042	0.055	0.040	-0.142	0.399	0.025**	0.012	0.837**	0.346	0.009	0.034
CSA inputs (1=yes)	-0.057	0.035	-0.036	0.044	-0.313	0.674	0.020**	0.010	0.443*	0.237	0.014*	0.007
Dummy for female holder	0.265***	0.049	0.080**	0.038	0.285***	0.058	-0.060***	0.017	-0.124***	0.030	-0.068***	0.011
Log (age of the holder)	3.341	11.925	1.615	5.683	3.384	11.920	-0.120	1.970	-0.709	2.755	1.677	2.127
Log (age squared of the holder)	-1.452	5.824	-0.738	2.768	-1.473	5.823	0.075	0.960	0.363	1.345	-0.803	1.038
Education of the head (1=literate)	-0.181***	0.038	-0.051**	0.025	-0.176***	0.042	0.028**	0.011	0.018	0.014	0.026***	0.008
Sex ratio in the HH (f/m)	-0.099***	0.018	-0.029***	0.011	-0.094***	0.019	0.015***	0.005	0.006	0.006	0.011***	0.004
Dependency ratio in the HH	0.073***	0.018	0.024*	0.014	0.077***	0.022	-0.047***	0.005	-0.050***	0.008	-0.034***	0.004
Log (household size)	0.205***	0.058	0.053	0.039	0.206***	0.058	-0.465***	0.020	-0.414***	0.021	-0.355***	0.012
Log (land size in hectares)	-0.440***	0.095	-0.120***	0.037	-0.492**	0.196	-0.008	0.020	0.047	0.051	0.010	0.018
Land tenure (1=owner)	0.007	0.042	0.004	0.022	0.042	0.111	0.002	0.012	-0.033	0.029	0.011	0.009
Wealth index	-0.094***	0.022	-0.025**	0.011	-0.085***	0.025	-0.008	0.005	0.029***	0.009	0.012***	0.004
Number of oxen (in TLU)	-0.471***	0.032	-0.128***	0.020	-0.461***	0.044	0.091***	0.008	0.047***	0.017	0.075***	0.006
Access to credit services (1=yes)	0.305	0.237	0.080	0.227	0.302	0.265	0.037***	0.010	-0.026	0.023	0.022***	0.009
Access to extension program (1=yes)	-0.100*	0.052	-0.046	0.030	0.000	0.215	0.037**	0.016	-0.443**	0.205	0.025	0.021
Log (rainfall in the growing season)	-0.638***	0.054	-0.187***	0.033	-0.633***	0.061	0.079***	0.012	0.011	0.026	0.065***	0.011
Log (temperature in the growing season)	-0.972***	0.197	-0.215	0.140	-1.142***	0.415	0.106**	0.046	0.603***	0.197	0.010	0.053
Terrain Roughness	0.027***	0.006	0.008**	0.004	0.026***	0.007	-0.006***	0.001	0.003	0.003	-0.002*	0.001
Potential Wetness Index	0.038***	0.010	0.011*	0.007	0.041***	0.012	-0.010***	0.002	-0.020***	0.005	-0.007***	0.002
Nutrient availability	0.329***	0.031	0.092***	0.021	0.302***	0.068	0.019**	0.008	0.074**	0.029	0.004	0.007

Workability (constraining field management)	-0.162***	0.017	-0.050***	0.011	-0.162***	0.019	0.022***	0.005	0.007	0.007	0.018***	0.004
Log (number of population of the community)	0.267***	0.033	0.079***	0.021	0.288***	0.067	0.008	0.009	-0.042*	0.022	0.001	0.007
Log (distance in to nearest population centre) (km)	0.015	0.027	0.006	0.018	-0.009	0.054	0.022***	0.008	0.074***	0.024	0.014**	0.006
Collective action for natural resource conservation (1=yes)	0.150***	0.035	0.042*	0.023	0.152***	0.035	-0.001	0.010	-0.016	0.012	-0.008	0.007
Regions (reference: Oromia)												
Tigray	-0.875***	0.077	-0.256***	0.053	-0.829***	0.133	-0.268***	0.019	-0.284***	0.027	-0.214***	0.016
Amhara	-0.633***	0.051	-0.190***	0.035	-0.630***	0.085	-0.159***	0.014	-0.091***	0.025	-0.122***	0.011
Somalie	-0.783***	0.109	-0.226***	0.056	-0.788***	0.121	-0.426***	0.020	-0.369***	0.024	-0.346***	0.022
Benshagul Gumuz	-0.157	0.124	-0.047	0.069	-0.128	0.139	-0.201***	0.033	-0.256***	0.042	-0.169***	0.026
SNNP	-0.414***	0.048	-0.126***	0.037	-0.409***	0.053	-0.103***	0.014	-0.140***	0.025	-0.094***	0.011
Harari	-2.064***	0.171	-0.399***	0.050	-1.946***	0.335	0.671***	0.032	0.464***	0.081	0.587***	0.020
Diredwa	-0.289***	0.084	-0.092	0.071	-0.316***	0.100	-0.230***	0.021	-0.137***	0.038	-0.194***	0.019
Constant	1.887	1.598	0.768	0.882	2.360	1.928	8.451***	0.304	7.399***	0.577	8.415***	0.315
/lnsig_1											-1.203***	0.008
/atanhrho_12					0.107	0.228					0.001	0.065
/atanhrho_13					0.154	0.420					0.001	
/atanhrho_23					-0.117***	0.023					-0.057**	0.023
Number of observations	8,480		8,480		8,480		8,480		8,480		8,480	
Adjusted/Pseudo R2	0.138		0.138				0.404					
Log-Likelihood	-4,327.48		-4,590.96		-12,676.24		-2,467,665.21				-10,177.59	

6. Conclusions and policy recommendations

This paper contributes to the literature on agricultural technology adoption generally, and specifically on farmers' incentives and conditioning factors that hinder or accelerate adaptation strategies and its impact on food security and net crop income in the context of Ethiopia. We use a novel data set that combines data from a large-scale representative household survey with historical rainfall and temperature data to understand how the climatic variables affect adoption of five main agricultural practices (chemical fertilizer, improved seeds, legume intercropping, organic fertilizer and anti-erosion measures) in Ethiopia by employing a multivariate probit technique that models simultaneous and interdependent adoption decisions and instrumental variables corroborated by conditional recursive mixed process estimators for the yield impact estimates.

The results support the notion of interdependency between the adoption decision of different farm management practices which may be attributed to complementarities or substitutability between the practices. The analysis carried out through the MVP model lead us to conclude that the determinants of the adoption of modern practices are generally different from those affecting risk reducing inputs such as CSA strategies. The results suggest the heterogeneity in adoption of farm management practices and accordingly, the unsuitability of aggregating them into one adaptation/ risk-mitigating variable. Results show that greater climate variability as represented by the coefficient of variation of rainfall increases adoption of risk-reducing inputs such as CSA measures, but reduces the use of inputs (such as chemical fertilizer) with uncertain benefits in terms reducing risk. For instance, in regions with greater variability in rainfall, more legume intercropping and anti-erosion measures are used, whereas the probability of adopting chemical fertilizer is low in areas where the rainfall variability is high. Wetter regions with lower maximum temperatures tend to use more chemical fertilizer whereas drier regions with higher temperatures favour CSA inputs. Even if higher climate risks do generate higher incentive to adopt, results also confirm the importance of other conventional constraints to adoption that need to be addressed.

Household wealth, plot level characteristics and access to rural institutions are found to be binding constraints in the adoption decision of most of the practices. Results point to the positive role of household wealth on the adoption decision suggesting that the higher the capacity of the household to absorb risk and finance an investment in additional activities, the greater the likelihood of adoption. Plot characteristics are also found to be important determinants of adoption for most of the practices. Land size is negatively related with adoption of the risk-reducing inputs but positively correlated with short term inputs like chemical fertilizer. Better tenure security increases the likelihood that farmers adopt strategies that will capture the returns from their investments in the long run and reduces the demand for inputs like chemical fertilizer and improved seed. Results also show the key role of rural institutions and community characteristics such as access to credit and extension services in governing the adoption decisions of households. The propensity of adopting chemical fertilizer, legume intercropping and organic fertilizer is higher for female plot holders confirming the crucial role of women in the Ethiopian agriculture.

The final piece of evidence comes from the impact estimates. CMP and IV estimations showed that the adoption of agricultural practices significantly improve farmer's income from on-farm activities but no significant impact on subjective food security indicator. Results also confirm the importance of other conventional correlates of crop income and the food security indicator. Climatic variables, plot characteristics and household demographics play a significant role in explaining variation in the outcome variables. Average precipitation and temperature during the rainy season is positively correlated with crop net income and food security. Crop net income and food security is significantly higher for households with a literate household head, smaller family size, male plot holders, a higher sex ratio and a lower dependency ratio.

We argue that investigating the impact of climate variability and other conditioning factors that hinder or accelerate adaptation strategies in rural Ethiopia provides useful insights on the role of climate patterns in farmers' production decision and also help in designing effective incentive structures to overcome barriers to adoption. The results of the analysis indicate that there is a need for improved design of and support of public policies for effective technology promotion to cope with the problem of climate variability, soil nutrient depletion and food insecurity. To make the adoption of these agricultural techniques more attracting for Ethiopian farmers, policy makers should make an effort to target women, guarantee more stable land tenure, improve access to credit services and improve extension programs. Based on the evidence that climatic condition plays an important role in farmers' adoption decisions, it is natural to conclude that improving the access to reliable climate forecast information is key to facilitating adaptation. Linking farmers to new sources of information on climate variability will be important, but translating the risks and potential margin of error that exist in a way that farmers can understand and use in decision making is equally important.

It is important to point out that we have not yet estimated the impact of adoption of these practices on reducing yield/income variability in the face of variable climate conditions. Increasing yields/income is just one of the reasons to adopt these technologies but reducing downside loss can be the other reason. Therefore the results should be interpreted with the caveat in mind. Future research will try to assess the role of adoption of CSA practices on yield/income variability under variable climate regimes by making use of panel data when possible. Finally we also cannot estimate the impact of adoption of various combinations of these practices on outcome variables in this paper. However this knowledge is relevant to the debate on whether farmers should adopt technologies piecemeal or in a package, and for designing effective extension policies by identifying a combination of technologies that deliver the highest payoff. Therefore, we recommend further research to also look at modelling impact analysis in a multiple technology choice framework to capture useful economic information contained in interdependent and simultaneous adoption decisions.

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Economics and Policy Innovations for Climate-Smart Agriculture (EPIC)
EPIC is a programme hosted by the Agricultural Development Economics Division (ESA) of the Food and Agriculture Organization of the United Nations (FAO). It supports countries in their transition to Climate-Smart Agriculture through sound socio-economic research and policy analysis on the interactions between agriculture, climate change and food security.

This paper has not been peer reviewed and has been produced to stimulate exchange of ideas and critical debate. It synthetizes EPIC's ongoing research on the synergies and tradeoffs among adaptation, mitigation and food security and the initial findings on the impacts, effects, costs and benefits as well as incentives and barriers to the adoption of climate-smart agricultural practices.

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