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CLIMATE CHANGE ADAPTATION STRATEGY AND ITS EFFECT ON FARMERS' DOWNSIDE RISK EXPOSURE IN THE NILE BASIN OF ETHIOPIA

BY

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ADDIS ABABA, ETHIOPIA

DECEMBER, 2015

ADDIS ABABA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

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Climate Change Adaptation Strategy and Its Effect on Farmers' Downside Risk Exposure in the Nile Basin of Ethiopia

A Thesis Submitted to the School of Graduate Studies of Addis Ababa University in Partial Fulfillment of the Requirements for the Degree of Master of Science in Economics (Resource and Environmental Economics Stream)

BY

Yechale Getu Endalew

Addis Ababa, Ethiopia

December, 2015

Declaration

I hereby declare that this thesis is my own work and has never been presented in any other university or I have not plagiarized in the preparation of this assignment and have not allowed anyone to copy my work. All sources of materials used for this thesis has been properly acknowledged.

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Date: 08/12/2015

As thesis advisor, I hereby confirm that this thesis is the output of research undertaken by Yechale Getu under my supervision and that it be submitted for the M.Sc. degree award.

Confirmed by Advisor: **Hailemariam Teklewold (PhD)**

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December, 2015

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This is to certify that the thesis prepared by Yechale Getu, entitled: Climate Change Adaptation Strategy and Its Effect on Farmers' Downside Risk Exposure in the Nile Basin of Ethiopia; and submitted in partial fulfillment of the requirement for the degree of Masters of Science in Economics (Resource and Environmental Economics) complies with the regulations of the university and meets the accepted standards with respect to originality and quality.

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ACKNOWLEDGEMENTS

First I would like to thank God Almighty, without his power and wisdom this study would not come to an end. I would like to offer my heartfelt thanks to my supervisor Dr. Hailemariam Teklewold for his guidance, patience, and constructive criticisms throughout the accomplishment of this thesis. Doctor, no words can explain my gratitude to your friendly supervision and without your guidance, it would have been impossible for me to overcome all the difficulties I faced for a year. Besides, I am grateful to Dr. Alemu Mekonnen, for initiating my interest towards such striking subject and the support for getting resources from IDRC through EDRI.

My special thanks also go to ECRC (Environment and climate research Centre) for its invaluable contribution to get farm household data used in this work and financial support through EDRI(Ethiopian development research institute) and IDRC(International development research Centre of Canada). And also I am grateful to ECRC staffs particularly Smueal Abera, Dr. Dawit Wubshet, and Zelalem G/medihn for their welcoming approach when I was in need of their assistance.

Last but not least I am indebted to those who helped me in different ways to the successful accomplishment of this thesis.

Yechale Getu Endalew

Addis Ababa, Ethiopia

December, 2015

ABSTRACT

This study examines factors determining adoption of AWM (Agricultural Water Management) and the effect of AWM on downside risk exposure of farmers in the Nile Basin of Ethiopia. Moment based specification of farm income function is employed to measure downside risk exposure. We apply an endogenous switching regression approach by modeling AWM and downside risk depending on household and farm characteristics and a set of climatic variables based on geo-referenced historical precipitation and temperature data. Our analysis is based on farm level data collected in 2015. The result indicated that household and farm characteristics, and institutional and climatic factors are the important factors explaining both the adoption of AWM and downside risk exposure. We found that adoption of AWM is more likely under warmer and moisture stress climatic conditions. The result also showed that adaptation to climate change through AWM play a significant and positive role in reducing the downside risk exposure of farm households. It is also found that transitional heterogeneity revealed that farm households who did not adopt AWM would have been benefited more than those who adopted AWM if they did adopt. Equally, farm households who did adopt AWM would have been exposed to downside risk exposure in a higher probability than those who did not adopt if they did not adopt. The finding from this study confirms that adoption of AWM is important for farmers to reduce the likelihood of crop failure. Therefore, the result suggests the adoption and diffusion of AWM in the Nile Basin areas to reduce the probability of crop failure and contract the deleterious effects of climate change.

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ACRONYMS

ADLI	Agricultural Development Led Industrialization
ATA	Agricultural Transformation Agency
AWM	Agricultural Water Management
CSA	Central Statistics Agency
ECRC	Environment and Climate Research Center
EDRI	Ethiopian Development Research Institute
FIML	Full Information Maximum Likelihood
GDP	Gross Domestic Product
GTZ	German Technical Cooperation
GPS	Global Positioning System
IDRC	International Development Research Center of Canada
IFPRI	International Food Policy Research Institute
IPCC	Intergovernmental Panel on Climate Change
MNL	Multinomial Logit
MOFED	Ministry of Finance and Economic Development
MoWR	Ministry of Water Resources
NMSA	National Meteorological Services Agency
OLS	Ordinary Least Squares
SNNP	Southern Nations Nationalities and Peoples
TLU	Tropical Livestock Unit
UNDP	United Nation Development Program
UNFAO	United Nation Food and Agriculture Organization

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CHAPTER ONE: INTRODUCTION

1.1. Background of the Study

Agriculture is the primary source of livelihoods for large number of households in sub-Saharan Africa where majority of them manage their own farms as farm operators with extremely small farm size. According to the report provided by United Nation Food and Agriculture Organization (UNFAO), more than 60% of population in sub-Saharan Africa and around 57% of them live in rural areas and work in agriculture accordingly (Eastwood et al, 2004). In Ethiopia agriculture is the major economic sector and backbone of the country's economy. For instance, about 46 percent of national GDP, 80 percent of exports, and 73 percent of employment are generated from the agricultural sector (ATA, 2014). Therefore, the performance Ethiopia's economy is closely associated with the performance of the agriculture sector which is largely rain fed.

Due to the combination of different factors such as drought, low level of advanced technology, and agriculture based economy; many people in developing countries including Ethiopia live with poverty and food insecurity. Economic performance of the country particularly the agricultural sector is usually uncertain, due to the biological nature of the agricultural sector in addition to relying on rain fed crop production and livestock rearing. They face many risks and uncertainties which arise from natural, economic and socio-political environments. The existence of these risks and uncertainties generate food shortages, deterioration in nutritional status and impoverishment for the people (Pinstrup-Anderson et al, 2001).

The variability of rainfall and nature dependence agriculture results in animal mortality due to livestock diseases and fluctuations in agricultural output and prices (Capitanio, 2008; World Bank

2010). These makes Ethiopia one of the poorest countries in the world caused by the risk of agricultural production and of reduced harvest and farm incomes (Dercon et al, 2005). Moreover, Ethiopia is considered as among the countries most vulnerable to climate change with the least capacity to respond in Africa (Orindi et al 2006). This implies that risks and uncertainties due to climate change play an important role in farmer's decision making which further affects agricultural productivity and growth. This makes adaptation to climate change is more urgent than ever.

Adaptation to climate change which can be defined as the '*adjustment in natural or human systems in response to actual or expected climatic stimulator and their effects, which moderates harm or exploits beneficial opportunities'* (IPCC 2007). It is identified as one of the policy options to reduce the negative impact of climate change on agricultural productions. Correspondingly, if replicated the adoption of yield increasing agricultural technologies, are expected to have a paramount importance for increasing productivity in African continent as it have resulted with what we call Green Revolution in Asia (World Bank, 2008). Moreover, adaptation strategies are helpful for reducing the exposure or for improving resilience in reaction to actual or expected changes and related extreme events (Adger *et al* 2007).

Different adaptation methods have been identified by the climate change research community. Use of new crop varieties and livestock species that are more suited to drier conditions, irrigation, crop diversification, mixed crop livestock farming systems, change of planting dates, diversification from farm to non-farm activities, increased use of water and soil conservation techniques, changed use of capital and labor, and trees planted for shade and shelter were the adaptation methods most commonly cited in literature (Bradshaw, Dolan, and Smit 2004; Kurukulasuriya and Mendelsohn 2006a; Maddison 2006; Nhemachena and Hassan2007).

As the capacity to adapt is very limited developing countries are generally considered most vulnerable to the effects of climate change than developed countries (Thomas and Twyman, 2005). Adoption of climate change adaptation strategies such as irrigation, crop diversification, mixed crop livestock farming systems, using different crop varieties, changing planting and harvesting dates are supposed to minimize the negative impacts of climate change on crop yields. In spite of the acknowledged benefits of these strategies in adapting to climate change, their uptake has been sluggish in Ethiopia and in other developing nations (Nhemachena and Hassan, 2007). According to Di Facalo *et al* (2011) in Ethiopia there is little evidence by crop producing smallholder farmers on adaptation to climate change and the factors that affect the adoption\choices of climate change adaptation strategies.

The Nile basin of Ethiopia is prone to extremes (e.g., drought and flood); resulted in crop failure, water shortage and food insecurity (Di Falco et al, 2011). This implies it is crucial to adopt climate adaptation mechanisms more importantly; agricultural water management in the study area in order to minimize the exposure of farmers from downside risk (crop failure).

Therefore, adoption of different strategies in order to minimize crop failure is believed to be a crucial strategy to solve the problem of extreme poverty in the region as almost all economic activities and economic agents are agriculture driving and agriculture based. Improving farm level resilience to agricultural production shocks through the adoption of different adaptation tools (such as AWM technologies) is essential in reducing crop failure in Ethiopia though limited adoption of these technologies in developing countries(Christiaensen and Demery 2007; Morris et al 2007). Agricultural water management is expected to be the major element in adapting such erratic and variable climate change (Besley, 1995). Theoretically; low adoption rates, low level of income and continuing beef poverty traps in many of these low income countries are frequently linked with risk exposure and risk avoidance (Rosenweig and Binswanger 1993).

1.2. Statement of the Problem

Improving farm level resilience to climate change and then agricultural shocks is essential to reduce production risk for the sub Saharan Africa which is exemplified by areas at high risk of climatic shocks with a high percentage of the population dependent on agriculture as Ethiopia. Ethiopia has been known with food insecurity, low-productivity in agriculture and drought due to climate change which is a major problem hobbling the agricultural sector (Bramel et al, 2004).Given high vulnerability to the negative effects of climate change, it is commonly thought that, it is possible to reduce its impact by developing different adaptation strategies. Moreover familiarity of the adaptation methods and determinants affecting farmers' choices can enhance essential policies which aim in attempting climate change challenges of smallholder farmers.

During the last forty years, Ethiopia has experienced severe droughts leading to production levels that fell short of basic subsistence levels for many farm households (Dercon, 2005). Harvest failure due to extreme weather events is the most important cause of risk related hardship of Ethiopian agricultural societies, with adverse effects on farm sector welfare (Dercon, 2005). More erratic and scarce rainfall and higher temperature imply that farmers will be facing a larger extent of uncertainty. Effective adaptation of agriculture to climate change is therefore crucial to address numerous types of risks associated with agriculturalists in Ethiopia (Lobell et al, 2011).

Risk to farmers could involve production, input and output prices, government programs and regulation, financing considerations, contractual arrangements, technology, or the environment. Understanding the relative importance of such various sources of risk is an important component of developing and implementing a risk management strategy for agriculturalists and effective adaptation of agriculture production to climate change (B.Fleisher, 1990). Risks affecting yield in main staple crops are particularly important for smallholders, who tend to consume a large part of their own production. In a rain fed agricultural production setting, avoiding crop failure is indeed the major preoccupation of farmers in Ethiopia.

Adaptation to climate change for a country is not an easy task as it needs to addresses the bigger problem of allocating scarce resources to attain sustainable development. Even though it is a difficult task in order to have sustainable economic growth for a certain nation application of different adaptation measures to climate change should not be ignored. Placing climate posed risks in the mainstream of development will be helpful for managing them more efficiently (GTZ, 2007).

Different initiatives have been implemented by government of Ethiopia to promote the adaptation of agriculture to climate change through its development strategy, known as Agricultural Development- Led Industrialization (ADLI). Despite such concerted efforts by the government, the adaptation mechanisms remains low and did not take in to account the different socio- cultural factors and farm operators' risk exposure (Shiferaw and Holden 2001). Moreover, given the current policy environment and the numerous sources of risk, research that examines the relative importance of factors contributing to risk particularly downside risk is needed. Downside risk may be more relevant to agricultural producers than other commonly used measures of risk, such as variability and producers concerned about downside risk need information pertaining to the determinants of downside risk (Tauer, 1983 and Atwood et al, 1988).

Despite the growing literature in agriculture related fields, farmers' downside risk exposure is frequently ignored in the evaluation of water conservation policies even if it is important in determining their production decisions. Unlike developing countries, in developed world increasing attention is being paid to downside risk exposure or risk associated with unfavorable events, such as climate change and financial shocks. Further, it is common knowledge that water management practices such as irrigation increases agricultural yields. It is also supposed to decrease the variability of yields, and hence the variability of income (Miyata, 2003).

Besides, even if there is now an extensive literature on the economic impacts of climate change, there are few studies that have examined the role of adaptation. Previous researches that examine factors contributing downside risk related to climate adaptation to agriculture with water management practice are available in developed countries. Among these a study by Koundouri et al (2006) in Greece and studies by Foudi and Erldlenbruch (2011) in France examined the adoption of irrigation in relation with risk. In the first study Koundouri et al (2006) concluded risk preferences affect the probability of adoption irrigation. In the second study farmers adopt irrigation technology in relation to the previous year's mean and variance of climate.

Having this, studies regarding climate change adaptation in relation with downside risk exposure have been conducted in Ethiopia in general and in the Nile basin of Ethiopia in particular. Furthermore, most studies in this area agree that adaptation methods result in farm household risk reduction. However, previous studies regarding this issue address the impact of climate adaptation mechanisms in a lump sum on farmer's downside risk exposure. That is, prior studies did not examine the impact of a single adaptation mechanism particularly AWM[1] on farmers' downside

[1] Note that: For this study AWM includes seven practices which are Broad Bed & Furrows, Water Wells, Ponds, River diversion, Micro dams, Irrigation, and Terracing. Therefore a farm household who adopted at least one of these practices is considered as adopter and otherwise non-adopter.

risk exposure. In this study an estimation of the effect of AWM on smallholder farm household downside risk exposure was done. A comparison of the estimated impacts of AWM on smallholder farmers‟ household among the adopters and non-adopters of AWM was also done. Our study which is conducted in the Nile basin of Ethiopia aims at tackling the following basic questions.

- What are the factors that determine adoption of agricultural water management and downside risk exposure?
- How the adoption of agricultural water management practice can influence downside risk exposure?
- Is there a difference in downside risk exposure of adopters and non-adopters of AWM in the counterfactual cases?

1.3. The Objective of the Study

The primary objective of this study is to investigate the effect of agricultural water management adoption on farm household's downside risk exposure in the Nile Basin of Ethiopia.

Specific Objectives:

Under the umbrella of the general objective, the followings specific objectives are addressed:

- To look into the determinants of AWM adoption and downside risk exposure.
- To explore the differences in downside risk exposure among the adopters and non-adopters of agricultural water management
- To realize the difference in downside risk exposure of adopters and non-adopters of AWM in the counterfactual cases.

1.4. Significance of the Study

It is expected that investments made by farmers are affected by risk. This implies that risk has an important implication to agriculture. In countries like Ethiopia where the share of agriculture in terms of GDP, employment and export is very high, risks in this sector would adversely affects the level of farm income in particular and the country's economy in general. Therefore, delivering information on the role of climate adaptation in farmers' risk management strategies especially using agricultural water management is essential. The identification of effective determinants of AWM practices and downside risk will inform decision makers and instruct policy on successful implementation of agricultural enhancement practices. Moreover, knowledge of the factors that determine farmers' decision to use AWM practices can enhance their ability to expertise AWM intervention measures to hedge themselves from production risk in general.

1.5. Limitation and Scope of study

This study is confined to the Nile Basin of Ethiopia, selected because it is part of the country where agriculture is the most important economic activity. It identified the variables that determine farmers' downside risk exposure, factors that influence farmers' adoption of agricultural water management, differences in risk exposure among the adopters and non-adopters and specifically focused on the effect of agricultural water management on downside risk exposure of farm households. Also the study is limited to a cross sectional data collected by ECRC in March 2015 on a total sample of 929 households and future studies can consider the dynamic aspect by taking data from the same sample on repeated time.

1.6. Organization of the Study

The remaining part of the thesis is organized as follows. Chapter two which presents a literature review provides the reader with an overview on the main previously published papers related to adaptation to climate change, agricultural technology adoption, and downside risk exposure. The third chapter presents the methodology. It describes the methodological choices made in this work and it also examines its validity and reliability. Chapter four analyzes the empirical data which are collected by the means of questionnaire. This study ends with chapter five in which the main findings of the study are concluded and some important policy implications are discussed.

CHAPTER TWO: LITERATURE REVIEW

2.1. Theoretical Literature Review

2.1.1. Downside Risk and Agriculture: Concepts and Measurements

Downside risk is risk that has some asymmetries in its distribution, being skewed to the lower value which is recurrent state in agricultural production. As average temperature and average rainfall are the main determinants for agricultural yield, deviations from optimal temperature or optimal rainfall have negative impacts on farm yields and so that on farm income. Having this situation, the distribution of yields tends to be biased towards the lower values and yields that are more likely to be below, or far below, its value during a “normal” season, than above or far above this value. Generally agricultural production is subject to many uncertainties. Any farm production decision plan is typically associated with multiple potential outcomes with different probabilities. Weather, market developments and other events cannot be controlled by the farmer but have a direct incidence on the returns from farming (Antón and rue André Pascal, 2008).

Risk considerations are necessary in the analysis of the agricultural sector. This is because of, number of possible cases where intelligent policy formulation should consider. Not only the marginal contribution of input use to the mean of output, but also the marginal reduction in the variance of output have to be the concern of the policy makers (Groom et al, 2008).

Risk has been primarily associated with the dispersion of the corresponding random variable and measuring the riskiness of an alternative using its variance or standard deviation is common. For a normally distributed outcome it is possible to define the distribution using mean and variance. However, higher order moments, particularly skewness and kurtosis, are required to have more information about the shape of the distribution (Berg E. and Michael Starp, 2006).

Even though it is possible to use variance of yields as a measure of risk exposure, this does not help to distinguish between unexpected good and bad events. Therefore, in order to distinguish between unexpected good and bad events skewness can be used in risk analysis to approximate downside risk exposure by the third moment of the crop yield distribution. As a measurement of downside risk exposure if the skewness of yield (income) increases and becomes positive, then it means that downside risk exposure (probability of crop failure) decreases (Di Falco and Chavas, 2009). Here skewness which is measured by the third central moment of a distribution is a measure of downside risk. The more right skewed a distribution, the greater is the probability-weighted sum of cubed deviations above the mean relative to those below it. Given equality of the means and variances, distributions which are more skewed to the right are regarded as providing better downside protection or smaller downside risk. Koundouri et al (2006) argue that the issue of risk has rarely been addressed adequately in the relevant literature concerning farmers' decision.

2.1.2. Agriculture, Climate Change, and Downside Risk

According to IPCC (2007) "*climate change refers to a change in the state of the climate that can be identified (e.g. using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer*". Simply it is an overtime change in climatic conditions either due to natural instability or as a result of human activity.

The existence of long-term water and other resource shortages, worsening soil conditions, drought and desertification, disease and pest outbreaks on crops and livestock, sea-level rise are the likely results of climate change. Reductions in agricultural productivity, which is largely due to a fall in crop yields, are the expected experiences of vulnerable areas (Rosenzweig et al, 2002). Therefore, as agriculture sector is rain-fed especially in developing countries the existence of unfavorable climate change leads downside risk exposure (crop failure).

The economies of many African nations are dependent on sectors such as agriculture, fisheries, forestry, and tourism that are vulnerable to climate conditions. Agriculture and natural resources provide the livelihood for 70% to 80% of the population, and account for 30% of GDP and 40% of export revenue in Sub-Saharan Africa (Toulmin and Huq, 2006). Given this statistics we can understand that the economy of Africa in general and sub Saharan Africa in particular is mostly dependent up on agriculture which is subject to risk and uncertainty due to climate change. Therefore, given a nation is agriculture dependent the sector will highly be affected by climate change and the change in climate will expose farm households to downside risk.

Extreme climatic situations like drought and flood are common in the Nile basin region. The presence of low precipitation for consecutive years makes large areas of the region in severe drought that resulted in crop failure (downside risk). Water shortage and serious food security concerns are the other results of the climate change in the region. Drought which is characterized by abnormal soil water insufficiency and mainly caused by natural climatic variability such as precipitation shortage or increased evapotranspiration is one of the major environmental catastrophes in the basin. Climatic factors have a large spatial and temporal variation, which makes prediction and monitory of drought events difficult (Su and Roerink, 2004). Nile basin of Ethiopia which is mostly agricultural area is not only subject to the predetermined climate shocks but also other shudders such as erratic rainfall, hailstorm, animal attack, and so on. Such events have a negative impact on the yield level of smallholder farmers'. Therefore there is a need to dig on this issue and have adaptation mechanisms in order to cope up such unforeseen occasions.

2.1.3. The concept of climate adaptation and adaptation strategies

It is known that peasants pass through high level of uncertainty provoked by natural hazards such as weather, pests, diseases, natural disasters in addition to market fluctuations; and social uncertainty in their production process (Ellis, 1992). The existence of such situations cause risks to peasant production and make farmers very careful in their decision making and therefore, farmers are generally assumed to be risk averse *(*Walker and Jodha, 1986).

Adaptation to climate change is "*the adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or, exploits beneficial opportunities*" IPCC (2007). IFPRI (2007) also defines adaptation as the process of improving society's ability to cope with changes in climatic conditions across time scales, from short term (e.g. seasonal to annual) to the long term (e.g. decades to centuries).

Regardless of its severity climate change is everywhere with its undesirable bearings. In order to minimize the negative impacts of climate change on agricultural productions adaptation is identified as one of the policy alternatives (Kurukulasuriya and Mendelsohn, 2006). Adaptation in agriculture can exist at two main scales. These are at macro level and micro level. Macro-level analysis is concerned all about adaptation for agricultural production at the national and regional scales and it's interlink with the internal as well as external policy (Bradshaw *et al*, 2004 and Nhemachena and Hassan, 2007). Macro-level or national level adaptation includes crop adaptation measures and reuse of water and combinations of both. However, some measures such as rain water harvesting can be practiced at the individual level or may require collective actions. Investments at national or government level may include building dams and releasing new cultivars that are more water efficient (Jawahar and Msangi, 2006).

Micro-level analysis of adaptations are those which can be practiced at household level by farmers with strategic actions in response to agriculture focuses on tactical decisions that farmers make in response to cyclical differences of climatic conditions. Adaptation options such as changing planting and harvesting dates, mixed crop- livestock farming mechanisms, new crop varieties and agricultural water management such as (irrigation, river diversion, micro dams, terracing etc.) are examples of household level adaptation mechanisms (Temesegen *et al,* 2008).

The focus of adaptation strategies and actions should be to secure well-being in the face of climate change and a wide variety of biophysical and social contingencies which are difficult to predict. Climate adaptation should focus on support for the decision-making and capacity building processes that shape social learning, technology transfer, innovation, and development pathways. Adaptation is most relevant when it influences decisions that exist irrespective of climate change, but which have long-term consequences (Stainforth et al, 2007).

A number of strategies can be used as a means of adaptation to climate change in agriculture. Bradshaw et al (2004) has mentioned a number of adaptation strategies, including crop diversification, mixed crop livestock farming systems, using different crop varieties, changing planting and harvesting dates, drought-resistant varieties and high-yield water sensitive crops. Di Falco et al (2011a) have identified changing crop varieties, adoption of soil and water conservation strategies for climate change adaptation in Nile basin area. Adjusting irrigation practices, crop varieties and livestock species to both temperature and precipitation levels as adaptation strategies are referred by (Wang et al, 2008).

Agricultural water management is among the climate change adaptation strategies which cover an increasingly wide range of technologies and practices available for improving water and land management. Agricultural water management is now a commonly accepted term to cover the range of technologies and practices whose objective is to ensure that adequate water is available in the root zone of crops when needed. It therefore includes capture and storage (in dams, in groundwater) as well as drainage of any water used for agriculture (crops, livestock, fish); lifting and transporting water from where it is captured to where it is used for agricultural production or removing excess water from where agriculture is practiced; and in-field application and management of water, including land management practices that affect water availability to crops (Merrey et al, 2006).

It (AWM) is an intentional human actions planned to use water at its optimal in producing agricultural products in the range from rain-fed systems to irrigated agriculture by using best fit technologies. Agricultural water management embraces extensive practices including *in situ* humidity conservation (e.g. mulching), and ex-situ water management (e.g. irrigation) (Awlachew *et al*, 2005). Thus, AWM is a broad term encompassing irrigation, drainage, water harvesting, water conservation, utilization of high water tables, as well as control of unnecessary evaporation, reduction of seepage losses, improving efficiency in water application, conveyance and utilization, and all aspects where water benefits the crop, livestock and ecosystems. “Management of agricultural water” is a better term describing the deliberate human actions, which ensure optimization of all types of water resource use for agricultural production.

Irrigation projects are the main forms of AWM and in Ethiopia this projects identified as large-scale irrigation if the size of command area is greater than 3,000 ha, medium scale if it falls in the range of 200 to 3,000 ha, and small scale if it is covering less than 200ha. In addition to the above classification according to (MOWR, 2002), the new developed classification includes the dimensions of time and management. This system distinguishes between four different types of irrigation schemes in Ethiopia: traditional, modern communal, modern private and public. More details on the different types can be found in (Werfring et al, 2004).

2.2. Empirical Literature Review

2.2.1. Determinants of adoption of agricultural technologies

There is a wide and detail empirical literature on the factors which affect the adoption of agricultural technologies. Socioeconomic dynamics (including sex, age, education, marital status) institutional factors (as information and credit access) and other factors affect the decision of farm households to use/choose among crop adaptation strategies which in turn affect downside risk exposure or crop failure (Di Falco *et al,* 2011).

Even if some of the studies hypothesized the difficulty of determining the effect of age on adopting adaptation strategies or farming technologies before empirical investigation most studies found a negative effect of age on agricultural technology adoption. A study by Kaguongo et al (2010) conducted using a binary logit model found a negative sign for age in adopting agricultural technology adoption. According to the results, if age of the household head increases by one year, the odds in favor of not adopting increases by 2.4%. According to authors' of this study the main reasons given for older people being less likely to adopt new technologies is that they are said to be less receptive to new ideas and are less willing to take risks. On the other hand, farm households with higher ages are expected to have more experience in farm production and adaptation measures even if there is the other way round of losing energy for production and taking adaptation options (Di Falco *et al*, 2011).

Regarding gender, studies by Asfaw and Admassie (2004) and Tenge and Hella (2004) pointed out that male households have a higher probability to take adaptation measures than female households. The two studies put their own investigation behind their generalization. In the first study males have higher probability of up taking new farming technologies as males have a higher probability of triumphing information about adaptation strategies and also undertake more risky projects than female headed households'. In the second study it was examined that women may have restricted access to information, land, and other resources due to traditional social barriers and this may result in low probability of females in adopting adaptation strategies. However, a study by Nhemachena and Hassan (2007) have contrary results with the above findings regarding gender of household heads, i.e. female headed households are more likely to adopt different methods of climate change adaptation than male headed households.

As of education, numerous studies argued that educated farm household are more likely to take adaptation strategies than those who are uneducated. Among these studies a study by Lin (1991) witnessed a positive relationship between the education level of the household head and the adoption level of improved technologies and climate change adaptation. Therefore, the more the farm household head educated the more to perceive climate change and take adaptation strategies and the reverse is true for uneducated. As such, studies by Maddison (2006) and Nhemachena and Hassan (2007) indicate that farming experience increases the probability of uptake of adaptation measures to climate change.

In the study by Temesgen et al (2008) access to climate change information and other extension services by farmers were found a positive significant factor adoption. Using probit model Temesgen et al (2008) examined the determinants of farmers' choice of adaptation methods and perceptions of climate change in the Nile basin of Ethiopia. Off farm income, male headed households, livestock ownership, household size, temperature and credit access were also the factors found with positive coefficients in determining the adoption of farming technologies.

However, Farm size and annual average precipitation are negatively related to adaptation. Therefore, lack of agricultural and climate information, being credit constrained, small number of household size and low level of temperature prevent farmers from adopting climate change adaptation strategies.

Other studies by Yirga (2007), Pattanayak*et al* (2003) and Caviglia-Harris (2002) observe that a positive relationship exists between the level of adoption and the availability of credit since credit eases the cash constraints and allows farmers to buy inputs such as fertilizer, improved crop varieties and irrigation facilities. As well, these studies also found a positive relationship between availability of credit and adaptation to climate change.

Another factor that influences the adoption of agricultural technologies is farmers' accessibility to the market places. A study by Maddison (2006) noted that long distances to market centers decrease the likelihood of farm adaptation and that market places provide important avenues for farmers to congregate (collect) and share information. In addition, Nyangena (2007) shows that in Kenya, distance to market places has a negative and significant effect on the adoption and use of soil and water conservation technologies. On the one hand, accessibility of input markets help farmers to have necessary inputs such as seeds, fertilizers, and agricultural water technologies used to take adaptation measures and the reverse is true if there is limited market access. On the other hand, the existence of output markets will allow farmers to produce cash crops that can help improve their resource base and hence their ability to respond to changes in climatic conditions. Consequently, those who have access to both input and output markets are likely to have more chances to use adaptation measures.

Using panel data Olwande et al (2009) conducted a study on the determinants of technology adoption and intensity of use. Olwande et al (2009) carried out their study using a double-hurdle model. Findings from this study showed that age, education of the farmer, access to credit, presence of a cash crop, distance to market and agro-ecological potential are among the factors which influence the probability of adoption. Moreover, intensity of technology adoption is found to be affected by gender of the farmer, dependency ratio, credit access, presence of cash crop, distance to extension services and agro-ecological potential.

Availability and quality resources can affect the participation of farm households in adaptation activities. For instance, farm households with more available and quality labor can have higher probability to get involved in climate adaptation activities (Kandlinkar and Risbey, 2000), and limited labor can constraint farmers from taking adaptation mechanisms. Therefore, households with more labor are believed to be better able to take adaptation measures in response to changes in climatic conditions and vice versa (Temesegen *et al*, 2008).

A study was conducted by Deressa et al (2009) on Factors affecting the choices of coping strategies for climate extremes in the Nile Basin of Ethiopia. Multinomial logit model was employed in order to identify socio economic and environmental factors expected to affect the ability of coping with different climate extreme events. The result of this study showed that gender of household head being male, age of the head of household which approximates experience, farm income, farm size, livestock ownership, extension on crop and livestock production, farmer-to-farmer extension, local agro ecology *kolla*, local agro ecology *weyna dega*, temperature and precipitation were the major determinants of adopting different coping strategies for climate extreme events.

A case study in rural Zimbabwe by Grothmann and Patt (2005) conducted using their own model examined processes of decision-making by subsistence farmers in four villages who had been given information about seasonal climate change and assessed the farmers' willingness to change their decisions on the basis of the information they received. In their findings farmers had no intention to adapt because farmers made no changes in response to the information. According to Grothmann and Patt (2005) the perception of low risk by farmers is among the factors that led to lack of attention towards adaptations.

A study by Nhemachena *et al* (2007) was conducted to examine the adaptation strategies used by farmers in response to climate change using a cross section data of three countries (South Africa, Zambia and Zimbabwe). This study which was conducted by employing a multivariate Probit model identified increased use of irrigation, changing planting and harvesting dates, crop varieties, and water and soil conservation mechanisms as the main adaptation strategies of climate change in the study area. Access to credit, extension and information on climate change forecasting were also recognized as important determinates of plot level adaptation by the predetermined strategies.

Bryan *et al* (2010) conducted a study on the adaptation techniques and the determinants of adopting these techniques used by farmers of Ethiopia and South Africa. In this study use of irrigation, altering planting dates, tree planting, soil conservation and crop varieties were identified as the common adaptation strategies of the two countries. Moreover, Access to extension, asset, access to credit, and climate change information were pointed as the major factors influencing farmers' decision for adaptation in Ethiopia. Whereas asset, government farm support, and access to fertile land and credit were among the factors which affect farmers' decision of climate change adaptation in South Africa.

With respect to temperature and rainfall Gbetibouo (2009) examined farmer's climate change perceptions and how it is related with recorded climate data with Heckman probit model and a multinomial logit (MNL) model. Using farm-level data collected from 794 households in the limpopo river basin of south Africa for the farming season 2004– 2005 the study analyzed farmers' adaptation responses to climate change and variability. Increasing temperature trend, and high inter annual rainfall variability were the major perceived changes by farmers of the study area. Switching crops, changing crop varieties, changing planting dates, increasing irrigation, building water-harvesting schemes, and changing the amount of land under cultivation, were identified as the major adaptation options of the area. Moreover, high temperature, and low rainfall were found factors which augment adaptive capacity to climate change.

Switching crop choice as a way of adaptation to climate change has acknowledged by Wang et al (2008). Taking 8,405 farmers in 28 provinces of China Wang et al (2008) found the existence of a positive relationship between irrigation and low levels of temperatures and precipitation. That is Chinese farmers are more likely to irrigate in case of lower temperatures and less precipitation. Farmers' choices of crops also vary with the levels of temperature. For instance, oil crops, maize, cotton and wheat are the chosen crops of the farmers in warmer places and vice versa for Vegetables, potatoes, sugar, rice and soybeans.

2.2.2. Effects of climate change on the lives of farm households

Several studies conducted in different countries to estimate the general effects of climate change. For instance empirical evidences by Skoufias et al (2011), suggests that climate change will slow the pace of global poverty reduction, but the expected poverty impact will be relatively modest and far from reversing the major decline in poverty that is expected to occur over the next 40 years as a result of continued economic growth. Therefore in addition to employment and income generation livelihood, food intake, health and education are also affected by the climate change.

Another study in Zambia by Thurlow et al (2009) on climate change by using dynamic computational general equilibrium model found that if rainfall declines by 15%, climate change enhances the negative effects of climate variability by a factor of 1.5. Moreover this pushes an additional 30,000 people below the poverty line over a 10-year period. This shows the cost of a decline in rainfall for Zambian economy.

Similarly a study by Kurukulasuriya and Ajwad (2007) conducted to estimate the effect of climate change on the smallholder agriculture sector in Sri Lanka applying the Ricardian technique where irrigation is taken as a strategy of climate adaptation. 1552 households were taken in the study and the results show that climate variables can explain about 14% of the variation in net revenues across farms. This result confirms the significant effect of climate change on the livelihoods of farm households'.

Even if climate change affects the development path of the world negatively its impact is not similar in developing and developed countries. It is widely agreed that developing countries are more vulnerable to climate change than developed countries mostly because of their proportionately larger agricultural sectors, with food security affected adversely. A study by Cline (2007) on the estimated impact of climate change on agriculture by country found Warming decrease production by accelerating growth speed and reducing their water consumption and Evaporation from topsoil increase, as does transpiration, again inducing moisture loss or evapotranspiration. This is partially counter by the increase in rainfall anticipated due to climate change.

A study by Kurukulasuriya P. and R. Mendelsohn (2007) examined the relationship between climate change and the decision to employ irrigation and then how climate change affects the net revenues of dryland and irrigated land. The Ricardian 'selection' model, using a modified

Heckman selection model is employed and estimated across 8400 farmers in Africa. Controlling for endogeneity irrigation is modeled explicitly. From the study it was found that the choice of irrigation is sensitive to both temperature and precipitation. The results also indicate that African agriculture is sensitive to climate change. Many farmers in Africa were experience net revenue losses from warming.

There is a study conducted by Lobell *et al* (2008) on the analysis of climate risks for crops in 12 food-insecure regions to identify adaptation priorities, using statistical crop models and climate projections for 2030 from 20 general circulation models. Outcomes of the study showed South Asia and Southern Africa, will likely suffer negative impacts on several crops that are important to large food-insecure human populations due to insufficient adaptation measures in these regions.

2.2.3. Climate change adaptation and downside risk exposure

Studies were also conducted both in developed and developing nations regarding climate adaptation by adopting various technologies in order to minimize downside risk that will come due to climate change. For example, Koundouri et al (2006) were analyzed a farmers' decision to adopt new irrigation technologies in Greece, using the flexible moment-based approach. The model is estimated based on a cross section of 265 farms. Results show that risk preferences affect the probability of adopting irrigation and provide evidence that farmers invest in new technologies as a means to hedge against input related production risk.

Similarly, Foudi and Erldlenbruch (2011) assessed the decision of the farmer to irrigate or not using a probit model in French. They expressed that farmers rely on irrigation technology as a self-insurance tool against production risk, particularly the risk of droughts. Finally, they conclude that farmers adopt irrigation technology in relation to the previous year's mean and variance of climate.

This means the adoption of irrigation by farm households as climate change adaptation mechanism was dependent up on the past climatic conditions of the study area.

Another study in France by Reynaud (2009) examined the way farmers manage drought risks through irrigation and crop diversification. Reynaud confirmed that comparing the two risk management strategies (irrigation and crop diversification) crop diversification is more efficient than irrigation in tempering possible revenue losses for French farmers. This result may not be consistent for all nations with different settings. However, from this result it is clear that the level of importance a given adaptation mechanism has in reducing downside risk may be different from another adaptation mechanism.

Moreover, Kurukulasuriya P. and R. Mendelsohn (2008) conducted study on adaptation and climate change impacts using structural Ricardian model of irrigation and farm income in Africa. The study is carried out using data from farmers across eleven African countries. Their result shows that the choice of irrigation is sensitive to both temperature and precipitation. Furthermore, rain fed and irrigated farm income respond to climate in different way. Even if irrigation is determined as endogenous in the study the choice is sensitive to Climate.

Pannell D. (1990) reviewed the role of risk in decision making for agricultural pest control. In the review it is identified that risk can affect pesticide decision making either because of risk aversion or because of its influence on expected profit. It is also summarized that individual farmers increased use of pesticide does not essentially guided by risk. However, the existence of uncertainty about some variables, such as pest density and pest mortality, does lead to higher optimal pesticide use if the farm household is risk averse. On the other hand, uncertainty about other important variables, such as output price and yield, leads to lower optimal levels of pesticide use.

Another study by Kassie M. et al (2014) on the impact of Sustainable Intensification Practices (SIPs) on farm households' food security, downside risk and the cost of risk in Malawi. A multinomial endogenous switching regression framework was employed to correct for the selection bias. From this study the authors found that adoption of Sustainable Intensification Practices reduce downside risk exposure. Moreover, larger reductions in downside risk exposure are found from simultaneous adoption of minimum tillage and crop rotation than the adoption of either of these practices. Finally, the encouragement of the adoption of agronomic and resource-management practices along with other risk mitigation strategies by production risk management agents was suggested in the study.

Di Falco and Veronesi (2011) accompanied a study on adaptation to climate change and risk exposure in the Nile Basin of Ethiopia. Using an endogenous switching regression model it was found that information sources of farm households in general and the provision of climate information both from formal and informal institutions in particular were found the major determinants of adaptation to climate change. It is also found that, among farm households that adapted to climate change the variables such as seeds, manure, and animals are significantly associated with an increase in the skewness, and so in a decrease in downside risk exposure, while infertile soils are associated with an increase in downside risk exposure. In this study all these factors do not significantly affect the downside risk exposure of farm households that did not adapt.

In Ethiopia Di Falco et al (2011a) have looked at the driving forces behind farm households' decisions to adapt to climate change, and the impact of adaptation on farm households' food productivity in the Nile basin of Ethiopia. Implementing a set of strategies including adoption of soil and water conservation strategies in response to long run changes in key climatic variables such as temperature and rainfall they investigate how farm households' decision to adapt, affects food crop productivity in Ethiopia. From this study they found higher food productivity for the farm households that adapted than that did not adapt to climate change which implies adaptation to climate change increases food productivity. It is also found in the counterfactual case the impact of adaptation on food productivity is smaller for the farm households that actually did adapt than for the farm households that did not adapt.

Another study in Ethiopia by Di Falco et al (2011b) explored the reaction of a set of strategies implemented on the field to long-term changes in environmental conditions. This survey based study is conducted in the Nile basin of Ethiopia using production function and Ricardian approach. From the results of this study, access to information and household characteristics such as household size, education level and age of the household head have positive response on the implementation of climate adaptation strategies. Moreover, it is found that downside risk exposure is reduced with the adoption of climate change adaptation strategies. This implies farm households that implemented climate change adaptation strategies get benefits in terms of decrease in downside risk (risk of crop failure).

Furthermore, Kassie et al (2008) were analyzed the impact of production risk on sustainable land-management technology adoption by moment-based approach , using two years of cross-sectional plot-level data collected in the Ethiopian highlands. Results revealed that impact of production risk varied by technology type. Production risks (variance and crop failure as measured by second and third central moments, respectively) had significant impact on fertilizer adoption and extent of adoption. However, this impact was not observed in adoption of conservation technology. On the other hand, expected return (as measured by the first central moment) had a positive significant impact on both fertilizer (adoption and intensity) and conservation adoption. Economic instruments that hedge against risk exposure, including downside risk and increase productivity, are important to promote adoption of improved technology and reduce poverty in Ethiopia.

By and large, different studies were conducted on identifying determinants of adoption of climate change adaptation strategy and on the impact of climate change. Some studies were also done on investigating the effects of adapting to climate change on downside risk exposure of farm households including in our study area by the model which is employed here. In studies conducted prior regarding the effect of adaptation on downside risk exposure, no attempt have been made in examining the effect of a particular adaptation mechanism especially AWM on downside risk exposure of farm households.

CHAPTER THREE: METHODOLOGY

3.1.Description of the Study Area

The study is conducted in the Nile basin of Ethiopia. Nile basin of Ethiopia is a very large area that covers about 34% of the total geographical region and almost 40% of the population of the entire country (Deressa et al, 2009). This area is equivalent with 358,889 km^2, on which 40% of the country's populations lives in. The basin covers six different regional states of Ethiopia with different proportions which is 38%, 24%, 15%, 11%, 7% and, 5% of the total land areas of Amhara, Oromiya, Benishangul-Gumz, Tigray, Gambella and Southern Nations Nationalities and Peoples respectively (MoWR, 1998). Moreover, three major rivers specifically: the Abbay River, originating from the central highlands; the Tekeze River, originating from the north-western parts of the country and the Baro-Akobo River, which originates from the southwestern part of the country are included in the basin.

Farming in the study area is characterized by small- holder subsistence farmers. Farmers use plough and animals' draught power which makes production very traditional. The major input in the production process (land preparation, planting, and post-harvest) is labor and the use of other inputs is very limited (Deressa et al, 2009).

3.2.Data Types and Sources

The study used primary data which has been collected using structured questionnaire on 929 farm households within the Nile basin of Ethiopia in 2015. The collected data comprises household characteristics, land characteristics, credit, social capital, and perceptions on climate change.

3.3.Sampling Frame and Techniques

The sampling frame considered traditional typology of agro-ecological zones in the country (namely, Dega,Woina-Dega, Kolla and Berha). Percent of cultivated land, degree of irrigation activity, average annual rainfall, rainfall variability, and vulnerability (number of food aid dependent population) were the set of characteristics by which the frame was developed to select sample districts purposely. The sampling frame selected woredas[2] in such a way that each class in the sample matched to the proportions for each class in the entire Nile basin of Ethiopia. Having these, twenty woredas were selected purposely and simple random sampling was then used in selecting one village from each woreda and fifty households from each village. . One of the survey instruments was in particular designed to capture farmers' perceptions and understanding on climate change, and their approaches for adaptation

3.4.Model Specification and Statistical Analysis

3.4.1 Conceptual Framework

The methodology used in this paper is emanated from Roy's models of self-selectivity (Cameron and Trivedi, 2005; Wooldridge, 2002; Maddala, 1983). Roy (1951) examined the consequences for the occupational distribution of earnings when there is individual heterogeneity in skills and individuals self-select between private and public jobs based on expected potential outcomes. Similarly, smallholder farmers are assumed to be heterogeneous such that they may tend to self-select to adopt AWM practices. But, farmers tend to choose between alternatives of adopting and not adopting according to which has the higher utility which in turn depends on the profit of farm households. Consider a risk averse farm household that produces output Y using inputs $\mathbf{R}$ under

[2] Note: An administrative division equivalent to a district.

risk through a production technology represented by a well-behaved stochastic production function $Y = g(R, v)$, where $\mathbf{v}$ is a vector of random variables representing risk, that is uncontrollable factors affecting output such as current changes in temperature and rainfall. The profit function of the producer can be written as:

$\pi = pg(R, v) - c(R)$, where $p > 0$ is the output price and $c(R)$ is the cost of inputs R. Assuming the utility of the producer (farmer) depends on profit and is characterized by a von Neumann-Morgenstern utility function. The expected utility of the farmer can be defined as (Pratt, 1964):

$$EU(\pi) = EU[pg(R, v) - c(R)] \quad \ldots \ldots \ldots \ldots \ldots (1)$$

Now the farmer is expected to maximize this utility function which depends on its profit level. The mathematical explanation of this maximization problem is expressed as follows:

Max $EU(\pi) = EU[pg(R, v) - c(R)]$

First order condition:

$$EU'\left[P\left(g'(R, v)\right) - c'(R)\right] = 0 \quad \ldots \ldots \ldots \ldots \ldots (2)$$

- $PE(g'(R, v)U') = c'(R)E(U')$
- $P[E\left(g'(R, v)\right)E(U') + cov(E(g'(R, v)U'))] = c'(R)E(U')$

Dividing both sides of this equation by $P/E(U'\ )$ we have;

- $E(g'(R, v)) + \ cov(E(g'(R, v)U'))/E(U') = c'(R)/P \quad \ldots \ldots \ldots \ldots \ldots (3)$

Where U' , is the change in utility of farm profit with respect to a change in farm profit and $c'(R)/P$ is the ratio of input price to output price. $g'(R, v)$is the first order derivative of the stochastic production function with respect to explanatory variables. If a farm household is risk-neutral, the second term in the left-hand side of equation (3) will vanish and the classical assumption is maintained. However, in our case it is assumed that farmers are risk averse and so that the second term in the left hand side of equation (3) is different from zero.

Empirically, solving equations (2) and (3) is difficult and estimating the impact of input choice on risk is the major challenge. Many studies (such as studies by Just and Pope, 1979, Di Falco and Chavas, 2006, Groom et al, 2008, Di Falco and Chavas, 2009,) start their analysis by specifying a stochastic revenue function and they have taken the cube of the residual as proxy for downside risk of farmers. Likewise, Antle (1983; 1987) proposed a flexible estimation approach that has the advantage of requiring only cross-sectional information on prices and input quantities, plus other observables, such as plot and household characteristics and endowments. According to this approach, maximizing the expected utility of farm income with respect to any input is equivalent to maximizing a function of moments of the distribution of ε, (Antle 1983; 1987). In our study, we computed the third central moment of our stochastic farm net income[3] function (here after the income function) and took it as a measure of downside risk exposure in analyzing the effect of AWM adoption on farmers' exposure to downside risk.

All results depend on the income function so that determining the functional form of this function is another challenge. As several studies (such as Antle, 1983, Kumbhakar and Tveterås, 2003, Groom et al, 2008), we use the quadratic form. We regressed the income on the first degree and square of some of the explanatory variables in case nonlinear relation is expected. As risk-averse decision makers have an incentive to reduce their risk exposure and agricultural water management is one of the inputs in R, and we run to see the effect of AWM on risk exposure.

[3] Note: Our net farm income is calculated as a difference between the revenue function and costs (labor cost, cost of seed, cost of inorganic fertilizer and costs of pesticide and herbicide). .

In case of “downside risk aversion[4]’’farmers are adversely affected by downside risk such as risk of crop failure and try to adopt strategies that reduce exposure to such risk (Menezes et al, 1980; Antle 1983).This is captured by the downside risk exposure which can be measured by the skewness[5] of farm income.

This in turn implies there is a need to answer the question of how adopting agricultural water management affects the third central moment (skewness) of the distribution of the income function. Generally, farmers with downside risk aversion have motivation to adopt management strategies that will positively affect the skewness of the distribution of income by reducing the probability of crop failure. Therefore, going beyond a mean– variance analysis in the investigation of the effects of agricultural water management is necessary. The probability distribution of the stochastic income function $I(R,v)$will be assessed by applying a moment-based approach (Antle, 1983), that is risk exposure is represented by the moments of the income function $I(R,v)$. Considering the econometric specification for $I(R,v)$:

$$I(R,v) = f_1(R,\beta_1) + \varepsilon \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

[4]Note: According to Menezes et al (1980) a rise in downside risk implies increasing the asymmetry or skewness of the risk distribution towards low outcomes, given both the mean and the variance constant. Moreover, a downside risk-averse decision maker is made worse off with such a change by definition.

[5]Note: Since the variance does not distinguish between unexpected good and bad events, we consider the skewness in risk analysis. That is, we approximate downside risk exposure by the third central moment of the farm income distribution. If the skewness of income increases then it means that downside risk exposure decreases, that is the probability of crop failure decreases.

Where $f_1(R,\beta_1) = E\,[I(R,v)]$ which is the mean of $I(R,v)$ and it represents the first central moment. $\varepsilon = I(R,v) - f_1(R,\beta_1)$, is a random variable with mean zero whose distribution is exogenous to farmers' actions.The higher moments of the income function can be expressed as;

$$E\{[I(R,v) - f_1(R,\beta_1)]^m/R\} = f_m(R,\beta_m) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (5)$$

For m=2, 3. In this case $f_2(R,\beta_2)$ is the second central moment which shows the variance, and $f_3(R,\beta_3)$ is the third central moment which is the skewness. This Moment based approach offers a flexible representation of inputs (if their prices do not incorporated in the income function such as land), past climatic factors, assets, farm household head and plot characteristics on the distribution of income with production uncertainty. It goes beyond standard mean–variance analysis by considering the effects on downside risk exposure through skewness. Commonly one expects the expected income function $f_1(R,\beta_1)$ in equation (5) to be rising and concave in inputs R. Nonetheless, the effects of inputs R on the variance and skewness of income is mainly an experimental concern. For instance from equation (3), the i^{th} input can be variance increasing, variance neutral, or variance decreasing as $\partial f_2/\partial R_i$>0, =0, or <0, accordingly. Likewise, the i^{th} input can affect downside risk exposure through its effect on skewness $f_3(R,\beta_3)$.The i^{th} input would contribute to decreasing (increasing) downside risk exposure when $\partial f_3/\partial R_i$>0 or <0. Reducing downside risk means decreasing the asymmetry (skewness) of the risk distribution toward high outcome, holding both means and variance constant (Menezes et al, 1980; Di Falco and Chavas 2009). Here our special interest is the effects of agricultural water management on skewness of income.

From an agricultural producer's viewpoint, the downside variation is the important aspect of risk that the farmer needs to minimize. More than anything, risk is really defined by the possibility of disaster (large bad surprises) and it is this downside risk where agents care about rather than the variability (Menezes et al., 1980). Hence, because the use of the estimated variance of a distribution as a measure of risk equally penalizes both the upside and downside risk involved in smallholder farming, we used skewness preference approximated by the third central moments of the farm income distribution in risk analysis. It is a measure of degree of asymmetry where the probability of income loss (downside risk) increases with decreasing skewness of income and that of upside risk increases with increasing skewness.

3.4.2. The empirical Model

An econometric model of climate change adaptation (by applying agricultural water management) and risk exposure is specified in this section. The functional forms of the model are grounded from a previous work in this area by Di Falco et al, (2011). The impact of agricultural water management on farm households' downside risk exposure can be easily examined by including a dummy variable equal to one if the farm household practice agricultural water management on the risk equation and then apply ordinary least squares. Nevertheless, since the adoption of agricultural water management practice is assumed to be exogenously determined while it is potentially endogenous this approach might yield biased estimates. This is due to the fact that the decision on whether to apply agricultural water management practice or not is voluntary and this in turn may be based on individual self-selection.

As farm households may decide to apply based on the expected benefits those who will apply may have systematically different characteristics from the farmers that will not apply. In addition, the decision of farmers (in the adoption of agricultural water management) and risk exposure will be affected by unobservable characteristics of farmers and their farm. This will result in inconsistent estimates of the effect of adaptation (through agricultural water management) on risk of crop failure. For example, if only the most skilled or motivated farmers chose to adopt and we fail to control for skills, then we will incur upward bias. Therefore, in order to detect the endogenity of farmers' decision endogenous switching regression model is employed. In particular, the climate change adaptation decision by AWM and its implications in terms of risk exposure is modeled having the criterion and continuous or substantive equation.

The effects of adoption on risk exposure are often determined by comparing relevant variables across households adopting AWM. This approach may be appropriate for controlled experiments but not for empirical analysis using observational data, because of self-selection. Farmers endogenously self-select themselves into adoption/non-adoption decisions, so decisions are likely to be influenced by unobservable characteristics (for example, expectation of income gain from adoption, managerial skills, motivation) that may be correlated with the outcomes of interest. The parameters of the risk function can be inconsistent if we fail to control for selectivity in AWM choice. This requires a selection correction estimation method. We apply an endogenous switching regression adoption effects approach following Dubin and McFadden (1984) and Bourguignon et al. (2007) to correct selection bias.

Endogenous Switching Regression Sketch

A representative risk averse farm household i chooses to implement AWM strategy if the expected utility from adopting is greater than from the expected utility of not adopting. I.e. $E\ [U(\pi_1)] > E[U(\pi_0)]$ where, E is the expectation operator, U(.) is the Von Neumann-Morgenstern utility function representing the farm household's preferences under risk, π_1 is the agricultural profit with

AWM practice and π_0 is agricultural profit without AWM practice[6]. Now let P^* be the latent variable that captures the expected benefits from AWM practice choice with respect to not practicing. Finally the criterion (selection) equation is described as follows:

$$P_i^* = X_i\alpha + \omega_i \text{ With } P_i = \begin{cases} 1 \; if P_i^* > 0 \\ 0 \; otherwise \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(6)}$$

Farm household i, will choose to practice ($P_i = 1$) through the implementation of agricultural water management strategy in response to long term changes in mean temperature and rainfall if $P_i^* > 0$, and will not practice otherwise. The vector **X** represents variables that affect the likelihood to practice such as the characteristics of the operating farm; farm head and farm household's characteristics; the presence of assets; past climatic factors; the experience of previous extreme events; whether farmers received information on climate; government and farmer-to-farmer extensions, which can be used as measures of access to information about adaptation strategies and other institutional factors such as credit and cooperative membership.

In overcoming the standard econometric method of using a pooled sample of AWM adopters and non-adopters, endogenous switching regression model framework for downside risk exposure which is proxied by the skwness index derived from the stochastic income function is employed. Accounting for endogenity and selection biases this measure can then be elicited in to two estimable functions where farmers face two regimes. (1) To practice AWM, (2) not to practice and is defined as follows;

$$\text{Regime 1: } y_{1i} = R_{1i}\beta_{1i} + \tau_{1i} \quad if \;\; P_i = 1 \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(7)}$$

[6]Note: Here the per hectare profit of the farmer is given by $\pi = Pg(R,V) - r'R$, where farmers yield is a function of R(variable inputs used in the production) and V(vector of random variables representing risk); p and r represent the output price vector and input price vector respectively.

Regime 2: $y_{2i} = R_{2i}\beta_{2i} + \tau_{2i} \quad if\ P_i = 0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots$ (8)

Where y_i represent the dependent variable which is the third central moment (skewness) $[f_3(R,\beta_3)]$ of income function given in equation (5) in the two regimes and R_{1i} *and* R_{2i}represents a vector of exogenous variables such as the past climatic factors, inputs, assets, farm households and plot characteristics included in **X**. β_1 *and* $\beta_2$are vectors of population parameters that will be estimated in the model using the survey data. Further our model relies on the assumption that the error terms in equations (6), (7) and (8) have a trivariate normal distribution, with zero mean and covariance matrix of:

$$\mathrm{cov}(\omega_i, \tau_{1i}, \tau_{2i}) = \begin{pmatrix} \delta_1^2 & \delta_{1\omega} & \delta_{2\omega} \\ \delta_{1\omega} & \delta_2^2 & * \\ \delta_{2\omega} & * & \delta_\omega^2 \end{pmatrix}$$

Where δ_1^2 and δ_2^2 are variances of the stochastic disturbance terms in the regime functions in equation (7) and (8). δ_ω^2 is the variance of the stochastic disturbance term in the selection equation shown as equation (6). $*$ represents the covariance of the stochastic disturbance terms in equation (7) and (8) while it is not determined as y_{1i} and y_{2i}cannot be observed simultaneously. $\delta_{1\omega}$ is the covariance of the error term of selection equation (ω_i) and the outcome equation of regime one(τ_{1i}). Likewise, $\delta_{2\omega}$ represent the covariance of the stochastic disturbance terms in the selection equation and the outcome equation of regime two (τ_{2i}). The variance for the error term in the selection equation (δ_ω^2) is assumed to be 1, since the coefficients are estimable only up to a scale factor (Maddala, 1983).

An important implication of the error structure is that, because the error term of the selection equation (6) $\omega_i$is correlated with the error terms of the regime equations (7) and (8) which are

$\tau_{1i}$and τ_{2i} the expected values of these two error terms conditional on the sample selection are nonzero.

Mathematically; $E[\tau_{1i}|P_i = 1] = \delta_{1\omega} \frac{\phi(X_i\alpha)}{\Phi(X_i\alpha)} = \delta_{1\omega}\lambda_{1i} and E[\tau_{2i}|P_i = 0] = -\delta_{2\omega} \frac{\phi(X_i\alpha)}{1-\Phi(X_i\alpha)} = \delta_{2\omega}\lambda_{2i}$ where $\phi(.)$ is the standard normal probability density function, $\Phi(.)$ the standard normal cumulative function, $\lambda_{1i} = \frac{\phi(X_i\alpha)}{\Phi(X_i\alpha)}and\lambda_{2i} = -\frac{\phi(X_i\alpha)}{1-\Phi(X_i\alpha)}$. If $\delta_{1\omega}^{'}$ and $\delta_{2\omega}^{'}$(estimated co variances) are statistically significant the decision to practice AWM and downside risk exposure are correlated which becomes an evidence for endogenous switching and in turn indicates the existence of sample selection bias. The above model described by equations (6) through (8) is what we call a "switching regression model with endogenous switching" (Maddala and Nelson, 1975).

Self-selection models that are estimated in a two stage procedure have been criticized for being sensitive to misspecification (Wu and Babcock 1998). The lack of identification is particularly a problem when variables affecting the adoption decisions (X) are the same as those affecting the subsequent outcome equations (R). This is because, though the correction terms are non-linear, this may not be sufficient in some cases and leading to problems of multicollinearity (Khanna 2001; Wu and Babcock 1998). Accordingly, to improve identifiability we established a set of selection instruments hypothesized to directly affect the adoption decisions but not the outcome variables: Government extension, farmer-to-farmer extension, information from radio, and, if received information in particular on climatic factors. A simple falsification test is established for the admissibility of these instruments. If a variable is a valid selection instrument, it affect the AWM decision but not the risk exposure. The results confirm that in nearly all cases the sets of instruments are successful at enabling identification.

An efficient method to estimate endogenous switching regression models is **full information maximum likelihood** estimation (Lee and Trost, 1978). The logarithmic likelihood function given the previous assumptions regarding the distribution of the error terms is:

$$\ln L_i = \sum_{i=1}^{N} P_i\left[\ln \phi\left(\frac{\tau_{1i}}{\delta_1}\right)\right] - \ln \delta_1 + \ln \Phi(\gamma_{1i}) + (1-P_i)\left[\ln \phi\left(\frac{\tau_{2i}}{\delta_2}\right) - \ln \delta_2 + \ln\left(1 - \Phi(\gamma_{2i})\right)\right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$$

Where $\gamma_{ij} = (\frac{X_i\alpha+\rho_j\tau_{ji}/\delta_1}{\sqrt{1-\rho_j^2}})$j= 1, 2 with ρ_j=the correlation coefficient between ω_i(the error term of the selection equation) and the error term$\tau_{ji}$of equations (7) and (8), accordingly.

After Mundlak (1978) and Wooldridge (2002) to control for unobservable characteristics, average of plot variant variables such as organic fertilizer, fertility index, slope index, altitude and shock index are inserted in the estimation of adoption and skewness functions.

Conditional Expectations, Treatment and Heterogeneity Effects

Using endogenous switching regression model it is possible to compare the expected downside risk exposure of farm households that practice AWM with respect to farm households that did not practice. It is also possible to investigate the expected downside risk exposure in the counterfactual hypothetical cases that the farm households who adopted AWM did not adopt, and the reverse for farm households who had not adopt AWM . The conditional expectations for downside risk exposure in the four cases can be expressed as:

$$E(y_{1i}/P_i = 1) = R_{1i}\beta_1 + \delta_{1\omega}\lambda_{1i} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (10)$$

$$E(y_{2i}/P_i = 0) = R_{2i}\beta_2 + \delta_{2\omega}\lambda_{2i} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (11)$$

$$E(y_{2i}/P_i = 1) = R_{1i}\,\beta_2 + \delta_{2\omega}\lambda_{1i} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (12)$$

$$E(y_{1i}/P_i = 0) = R_{2i}\beta_1 + \delta_{1\omega}\lambda_{2i} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (13)$$

The effect of adoption of AWM on the adopters (TT) is calculated as the difference between (10) and (12) as:

$$TT = E(y_{1i}/P_i = 1) - E(y_{2i}/P_i = 1) = R_{1i}(\beta_1 - \beta_2) + (\delta_{1\omega} - \delta_{2\omega})\lambda_{1i} \dots\dots\dots\dots\dots\dots\dots (14)$$

This signifies the effect of climate change adaptation by AWM practice on downside risk exposure of the farm households that adopts AWM.

The effect of adoption of AWM for the non-adopter (TU) is calculated in the same way as the difference between (13) and (11).

$$TU = E(y_{1i}/P_i = 0) - E(y_{2i}/P_i = 0) = R_{2i}(\beta_1 - \beta_2) + (\delta_{1\omega} - \delta_{2\omega})\lambda_{2i} \dots\dots\dots\dots\dots\dots (15)$$

In order to calculate heterogeneity effects We followed Carter and Milon (2005) and define as "the effect of base heterogeneity" for the group of farm households that decided to practice as the difference between (10) and (13),

$$BH_1 = E(y_{1i}/P_i = 1) - E(y_{2i}/P_i = 0) = (R_{1i} - R_{2i})\beta_{1i} + \delta_{1\omega}(\lambda_{1i} - \lambda_{2i}) \dots\dots\dots\dots\dots\dots (16)$$

For the group of farm households that decided not to practice, "the effect of base heterogeneity" is the difference between (12) and (11), which can be expressed as;

$$BH_2 = E(y_{2i}/P_i = 1) - E(y_{2i}/P_i = 0) = (R_{1i} - R_{2i})\beta_{2i} + \delta_{2\omega}(\lambda_{1i} - \lambda_{2i}) \dots\dots\dots\dots\dots\dots (17)$$

The difference between (TT) and (TU) in equation (14) and (15) represents the so called "transitional heterogeneity" (TH) which indicates whether the effect of practicing AWM is larger or smaller for the adopters than for the non-adopters.

3.4.3. Description of Explanatory Variables and prior expectation

A set of socioeconomic and environmental factors are included in the empirical models. Household head characteristics such as age, sex, literacy, family size and marital status, plot characteristics such as, fertility index, slope index, and altitude of the plot, and farm size are among the explanatory variables of this study. Moreover, household off-farm job, remittance from relatives, access to credit, climate shock, livestock, productive farm asset, crop varieties, rainfall, temperature, and Co-operative involvement are also included. The dependent variables of this study are AWM and skewness. The description, type, value and expected sign (depending on previous literatures) on adoption of AWM and skewness are given in the following Table.

Table 1 Description of explanatory variables

Variable	Description and Variable type	Value	Expected Sign [7]	
			Adoption	Risk exposure
Household characteristics				
Remittance	Dummy variable remittance obtained from relatives	1 if remittance was received, 0 otherwise	+	+
Marital status	Marital status of the farm head	1 if married, 0 otherwise	(±)	(±)
Gender	Sex of the head of the farm household: dummy	1= male, 0= Female	(±)	(±)
Literacy	Education status of the farm head	1= literate, 0= Illiterate	+	+
Household size	Number of members of a household: continuous	Number	(±)	
Off farm employment	Income from off-farm activities during the survey year	1=yes, 0=no	(±)	(±)
Age	Age of the household head: continuous	Years	(±)	(±)
Assets				
Farm size	Size of farm in owned by the household: continuous	Hectare	(±)	+
VPFA	Value of productive farm asset: continuous	Birr	+	+
TLU[8]	Tropical livestock unit: continuous	Weight	(±)	(±)

[7] Note: += Positive, - =Negative and (±) = ambiguous or difficult to decide on the sign prior empirical investigation.

[8]Note: TLU (Tropical livestock unit) is a common unit to describe livestock numbers of various species as a single figure that expresses the total amount of livestock present – irrespective of the specific composition.

Input [9]				
Organic fertilizer	Amount of compost and manure per hectare: continuous	Kilogram		(±)
Plot characteristics				
Fertility index[10]	Index of fertility of the plot: continuous	Number	+	+
Slope index	Index of fertility of the plot: continuous	Number	-	-
Altitude	Altitude of the plot: continuous	Meters	+	+
Shock index[11]	Index of shocks happened in the plot: continuous	Number	+	-
Institutional factors				
Certification	If the plot of the farmer is certified : dummy	1=yes, 0= otherwise	+	+
Cooperative membership	If a household is a member to agricultural cooperatives: dummy	1=yes, 0= otherwise	+	+
Credit	If a household have access to credit service : dummy	1=yes, 0= otherwise	+	+
Climate information	If household gets information about climate from any source : dummy	1=yes, 0= otherwise	+	
Media information	If household gets information about climate from media (radio, television) : dummy	1=yes, 0= otherwise	+	

[9] Note: We cannot deduct the value of organic fertilizer from farm revenue function as it is difficult to find a price for it. This is due to the fact that nutrient ratios, nitrogen availability, ease of use, and cost can vary widely among materials. That is why we consider organic fertilizer explicitly as input of crop production.

[10] Note: Fertility index is derived from farmers' perception of their plots as highly fertile, moderately fertile and infertile by giving 1, 2, and 3 for infertile, moderately fertile and highly fertile plots respectively and then dividing it by three. The same procedure is followed to have the slope index.

[11] Note: Shock index is calculated by dividing shocks happened in a plot to the seven shocks which are given to farmers as alternative to answer whether they are happened or not. These shocks are drought, flood, erratic rainfall, pattern animal attack, landslide, hailstorms, and other shock specified by the respondent.

Government extension	If household gets information about climate from government extension: dummy	1=yes, 0= otherwise	+	
Neighbor information	If household gets information about climate from neighbor : dummy	1=yes, 0= otherwise	+	
Market distance	Distance between a farmer's house and the nearest market.	Minutes	-	
Climatic factors				
tem0013	average temperature (°C) 2000- 2013: continuous	Number	+	+
mmrainf0013	Average annual rainfall in (mm) 2000 – 2013: continuous	Number	-	+
Crop groups				
Cereal dummy	If the farmer grows cereal crops on the plot: dummy	1=yes, 0= otherwise	-	(±)
Plus dummy	If the farmer grows pulses: dummy	1=yes, 0= otherwise	-	(±)
Vegetable and fruit dummy	If the farmer grows Vegetables and fruits: dummy	1=yes, 0= otherwise		

CHAPTER FOUR: RESULTS AND DISCUSSIONS

In this section, both descriptive and econometric results generated in this study are presented and discussed. In the first section, descriptive analysis of the study are presented and discussed. In the second section, model results are presented and discussed.

4.1. Descriptive Statistics

It is thought that demographic characteristics and socioeconomic variables of sampled households were relevant in providing intuitions about the general features of the area under examination. Therefore, attempts made to incorporate and describe some important socioeconomic and demographic characteristics of sample respondents such as remittance, household size, literacy level, sex, age, and off farm employment. The mean of these variables are given in Table 2 below for the total, adopters and the non-adopters of AWM separately. As can be seen below 10, 15 and 6 percent of total respondents, adopters of AWM and non-adopters have gained remittance from their relatives or kinships in the survey respectively.

The statistic indicates that average household size for the sample household were around 5.3 for the whole sample with 6.2 and 4.7 for adopters and non- adopters respectively. Average household size of total sampled farm households is slightly greater than the national average 5.24 of 2009 data (CSA, 2009). Further, farm households who have adopted AWM have more active household members than those who did not adopt in average. From this it is possible to deduct compared with small, farm households with large active household members can participate actively in agricultural works such as AWM. This is consistent with the result found by (Askal, 2010).

Among the sample household heads 52, 63 and 45 percent of them were found literate for the total, adopters and non-adopters with the given order where by respondents did attend formal education at least for a year and can write and read. Hence around 48 percent of sampled households were found illiterate which may restrict the probability of finding agricultural information and this in turn will minimize the likelihood of taking up adaptation mechanisms. Respondents had found with an average age of around 51. Major difference is not found on average age of farm households who adopted and did not adopt AWM.

Even if farmers do farming as a major means of livelihood, some farmers or members of farm households also engaged in off-farm activities such as petty trading to compromise losses in agricultural production. Among the sample respondents 85 and 80 percent of them were male and married respectively. The proportion of marital status and male headed farm households is found a little bit higher for the group of adopters compared with non-adopters.

Average land holding of farm households is found 1.85 hectare per household for the total sample, while it is found 1.78 and 1.90 hectare for adopters and non-adopters of AWM with the given order. Average land holding of sampled farm households is greater than the average national arable land holding size per household of 1.18 hectare (CSA, 2007). The productive farm asset is valued in Birr and found around 2069 per household. The mean value of this productive farm asset is found higher for those who adopted AWM (birr 2172) compared with those who did not adopt (birr 2002). This implies the likelihood of adopting AWM found higher for farm households with higher productive farm asset than those with lower productive farm asset in average. Ownership of livestock is determined using tropical livestock unit in order to have a uniform measurement for all types of livestock. The mean livestock unit for the whole sample, adopters and non-adopters is found only slightly different.

Among the total respondents, 77 percent of sample households have access to credit and 55 percent of the sample households were found members of agricultural cooperatives'. Becoming part of agricultural cooperative is expected to expose farmers for information related with adoption and it can also ease the accessibility those inputs used for adoption which will be distributed through these cooperatives. Table 2 below also shows proportion of sample households who were part of agricultural cooperatives is much higher for adopters associated with the non-adopters.

Access to credit is one way of improving farm households' access to new production technology such as AWM. Credit access curtail the liquidity problem of farm household to purchase inputs used for the adaptation purpose. When a farm household runs to adopt an agricultural water management technology she/he will face a shortage of finance to purchase different materials such as water pumps and generators. In this case the farmer can have such instruments of adaptation through credit so that adoption is suggested to rise with credit access and the result in table 2 below is in line with this as mean level of credit access is higher for adopters.

As well, access to climate information and agricultural information from different sources for the sampled households is also presented at the same table below. The descriptive statistics shows access for most of these variables is higher for adopters than the non-adopters. Market access is the other factor taken in descriptive as well as in empirical analysis. The time (in waking minutes) by which farm households reach to the nearest market where they can access inputs and sold outputs is taken as a proxy of market access. The result in the descriptive statistics shows that in average the nearest market takes a walking time of around 53 minutes for the total sample but it is around 50 and 55 minutes for adopters and non-adopters respectively.

The study incorporates sample households from five regions which are Amhara, Oromia, Tigray, Benishangul-Gumuz, and SNNP. Around 64 percent of sample households were from Amhara and

Oromia regions with around equal shares and 16 and 15 percent of sampled farmers were from Tigray and Benishangul-Gumuz respectively. The remaining 5 percent of the sample is taken from SNNP. As of the total sample adopters of AWM vary from one region to the other. Oromia region have the lion share of farm households who adopted AWM by around 42 percent from the total adopters in the sample. This is followed by Amhara (31 percent), Tigray (15 percent) and Benishangul-Gumuz (11 percent).

Table 2 Descriptive Statistics of household level variables

Variable	mean		
	Total sample	Adopters	Non-adopters
Household characteristics			
Remittance	0.10	0.15	0.06
Marital status	0.80	0.84	0.77
Gender	0.85	0.88	0.84
Literacy	0.52	0.63	0.45
Household size	5.26	6.16	4.67
Off farm employment	0.33	0.35	0.31
Age	51.36	51.87	51.04
Assets			
Farm size	1.85	1.78	1.90
VPFA	2069.46	2172.41	2002.68
TLU	5.31	5.45	5.21
Institutional factors			
Cooperative membership	0.55	0.89	0.33
Credit	0.77	0.92	0.68
Climate information	0.71	0.86	0.60
Media information	0.83	0. 78	0.87
Government extension	0.49	0.52	0.47
Neighbor information	0.90	0.86	0.92
Market distance	53.61	50.72	55.49
Regional composition			
Tigray	0.16	0.15	0.17
Amhara	0.32	0.31	0.32
Oromia	0.32	0.42	0.26
Benishangul-Gumuz	0.15	0.11	0.17
SNNP	0.05	0.01	0.08

Sample size	821	323	498

Source: Author’s calculation from survey (2015)

4.1.1. Plot characteristics

Plot level characteristics considered in this study include plot slope, fertility, altitude, and shock index. A total of 4198 plots for 821 households are included in the study where the plots with smallest and largest area are 0.01 and 5 hectares. Soil fertility of plots were placed on three levels based on farmers’ perception. On average 37 percent of the sampled plots are perceived by farmers as highly fertile which can produce a lot in normal situations. The remaining 53 and 10 percent of the plots are perceived as moderately fertile and infertile respectively. Fifty one percent of the plots where AWM is adopted are under the group of moderately fertile soil and the remaining 41 and 8 percent of plots are from highly fertile and infertile correspondingly. Similarly, the slope of sample plots also grouped under ranks three depending on farmers’ perception as flat, slightly steep and steep. Sixty percent of the plots are found with flat slope and AWM is found adopted most on plots of flat slope.

Seven shocks are asked for sampled household by saying which shocks faced in the past and on which plot the shocks happened. Then, shock index is computed by dividing the number of shocks happened in a plot to the total shocks which are expected to face farmers. The shock index goes from 0 to 1 and as the shock index nears to 1 it means more shocks happened in that plot than the plot where the shock index approaches to 0. A plot with 0 shock-index implies no shock happened in the past on that plot and if it is 1 it means all the seven shocks happened in that plot. As it can be seen in the Table average shock index is more (0.18) for those who adopted AWM than those who did not adopt (0.17). This may be due to farm households adopt AWM on the plot which faced shocks than on plots on which shocks did not happened.

Households were also asked whether the plots are certified or not. Eighty four percent of the plots from the total were certified and the remaining 16 percent were not.

It is expected that the contribution of AWM adoption will not be similar for all crop types and in order to consider this difference we categorize the total crops in to three groups. These are cereal group, pulse group and vegetable and fruit group. Seventy six percent of the sample plots were planted with cereal crops and 18 and 6 percent of the plots planted with pulses and vegetable and fruits respectively in survey year. Comparing with the mean values in the total sample with the respective mean values in the adopters only vegetable and fruit groups have higher mean values for the adopters than the mean values of the total sample as well as the mean values of the non-adopters.

Table 3 Descriptive Statistics of plot level variables

Variable	mean		
	Total sample	Adopters	Non-adopters
Plot characteristics			
Highly fertile soil	0.37	0.41	0.35
Moderately fertile soil	0.53	0.51	0.54
Infertile soil	0.10	0.09	0.11
Flat slope	0.60	0.64	0.57
Slightly steep slope	0.37	0.33	0.39
Steep slope	0.03	0.03	0.04
Altitude	2220	2236	2210
Certification	0.84	0.86	0.83
Shock index	0.17	0.18	0.17
Crop groups			
Cereal dummy	0.76	0.75	0.76
Pulse dummy	0.18	0.16	0.19
Vegetable and fruit dummy	0.06	0.08	0.05
Sample size	**4198**	**1617**	**2581**

Source: Author's calculation from survey (2015)

4.1.2. Climatic factors

Local climatic conditions and agro-ecological conditions are expected to influence the decision of adopting AWM. We included district level climate variables (mean temperature and mean rainfall) in the model. Average monthly temperature and average annual rainfall from the year 2000 to 2013 are the climatic variables taken in this study with their square values. The mean value of average mean temperature is found around 20.38, 19.79 and 20.02 degree Celsius for the plots by which AWM adopted, not adopted and total sample plots respectively. Mean of Average rainfall is found around 684, 718 and 697 mm for the plots by which AWM adopted, did not adopted and for the total sample with the same order. Mean temperature is found higher for adopters of AWM than the non-adopters and the reverse is bring into being for mean annual rainfall.

Table 4 Descriptive Statistics of climatic variables

Variable	mean		
	Total sample	Adopters	Non-adopters
Climatic factors			
tem0013	20.02	20.38	19.79
mmrainf0013	697.07	684.10	717.77
Sample size	**20**	**20**	**20**

Source: Author's calculation from survey (2015)

One part of the survey asked respondents whether they perceive climate change throughout their life time. Ninety two percent of respondents perceived changes in climate and the remaining 8 percent did not perceived a change in climate throughout their life time. Considerable difference in climate change perception among the households who adopted AWM and did not adopt was not found. Beyond changes in overall climate conditions, respondents have indicated varying perceptions towards different climatic elements. These included increased and decreased in mean temperature and rainfall and other changes such as erratic rainfall and hailstorms. Among those who noticed changes in climate around 60, and 58 percent of the respondents perceived an increase in mean temperature level and a decrease in rainfall respectively. Like the climate change perception case there is no a significant difference between adopters and non-adopters of AWM towards perceiving a rise in mean temperature and a decline in rainfall level.

Regarding perceiving reduction mean temperature level only around 9 percent of respondents saw a decline in the level of mean temperature. The special thing here is the perception of households on a rise in rainfall level is found different between farm households who adopted and who did not adopt AWM. Around 26 percent of farm households who adopted AWM perceived a rise in rainfall level while only 17 percent of the respondents who did not adopt AWM have the same perception. On the other hand, the minority (10 and 22 percent) of the respondents perceived a decline and rise level of mean rainfall and mean temperature with the given order. Around 7.5 percent of the respondents saw other changes as erratic rainfall and hailstorms. From farmers' perception, we can generalize that there is a change in climate of the study area and the change which is common to most of the respondents was an increased mean temperature and a decreased rainfall.

As agriculture is sensitive to the change in climate raising the level of productivity or sustaining what is produced currently to the future is unthinkable, given there is a noticed climate change and variability. Different mechanisms or adaptation mechanisms can be adopted depending on different factors which determine the adoption level and type. Studies by Nhemachena *et al* (2007) and Bryan *et al* (2010) showed that planting different crop varieties, crop diversification, changing planting dates, and soil and water conservation are the major adaptation mechanisms taken by farmers in response to climate change impacts in Africa including Ethiopia.

In our study in addition to the perception of changes and types of noticed changes respondents were also asked about the adaptation mechanisms that have been taken individually and in group in response to the noticed long term changes in mean temperature and mean rainfall. Farm households who perceived a long term change in mean temperature and mean rainfall took different adaptation mechanisms in response to these changes. The adaptation mechanisms include both individual and group based. The major crop adjustment mechanisms are presented in Table 4 below.

Changing crop type and variety, changing planting dates of crops, soil and water conservation techniques and change in fertilizer application (either increasing or decreasing) are the major mechanisms which are taken by individual farm households in response to past climatic changes. Thirty two and 17 percent of respondent farm households have taken the change in crop type and variety and the change in planting dates as crop adjustment mechanisms respectively. Forty three percent of the respondents practiced soil and water conservation as an adaptation mechanisms where as 14 percent of farm households' change their fertilizer application.

Regarding group based adaptation planting trees (44 percent), planting indigenous crops (24 percent), protecting springs (23 percent), and startup tree nurseries (10 percent) were found as the major strategies.

From these results we can generalize that planting trees and soil and water conservation mechanisms are the dominant group based and individual based adaptation mechanisms for climate change in the study area with the given order.

Table 5 Individual and group based adaptation mechanisms

Individual based	Mean	group based	Mean
Changing crop type and variety	0.32	Planting trees	0.44
Changing planting dates	0.17	Planting indigenous crops	0.24
Soil and water conservation	0.43	Protecting springs	0.23
Changing fertilizer application	0.14	Startup tree nurseries	0.10
Sample size	821	821	

Source: Author's calculation from survey (2015)

Factors including household characteristics, socioeconomic factors, plot characteristics, institutional factors, and location dummies can determine the adoption of agricultural water management. Having this, figure 1 below shows the adoption of agricultural water management at plot level by region. The mean level of adoption of agricultural water management varies from one region to the other region. The mean level of adoption is the largest in Oromia region (51 percent) and the lowest mean adoption AWM is in SNNP (9.1 percent)[12]. Following Oromia, Amhara and Benshangul-Gumz adopted AWM in higher proportion than Tigray and SNNP.

[12] Note: The mean adoption at plot level is calculated with respect to the sample numbers of each region. For example mean agricultural water management adoption for Tigray = (number of plots with adoption of AWM in Tigray/number of samples plots from Tigray) and multiplied by 100 to change it to percent.

Figure 1 AWM adoption by regions

Source: Author's calculation from survey (2015)

4.2.Empirical Results

Estimates of the endogenous switching regression model by full information maximum likelihood using Stata 13 for the farm income and risk functions plus other tests such as treatment effects and instrument validity tests are presented in the following sections. Since skewness (i.e. the measure of downside risk exposure) have to be derived from the farm income function, estimation of farm income function is the first step of our empirical analysis. Most variables used in the estimation have got the expected sign and the overall statistical significance of the estimated model is found good. Climatic factors (mean temperature and mean rainfall), household characteristics (marital status, sex, credit access, cooperative membership etc.), and plot characteristics such as slope and altitude were found the main determinants of farm income for farm households who adopted AWM. (See in appendix A1)

4.2.2. Parameter estimates of AWM and downside risk exposure

Estimation results of the endogenous switching regression model for downside risk exposure are presented below in three tables (table 6, table 7, and table 8). Column (1) of the three tables report OLS regression results with a dummy variable of AWM adoption which equals 1 if the smallholder farm household adopted, and equals 0 if the smallholder farm household did not adopt it. Column (2) of the three tables shows estimated coefficients of the selection equation while columns (3) and (4) of these tables state results of the outcome equations for AWM adopters and non-adopters respectively.

4.2.2.1. Determinants of AWM Adoption[13]

Estimation results for the determinants of the adoption of AWM in the selection equation is presented in the second column of the tables below (table 6, table 7, and table 8). Attention should be paid to augment the adoption of AWM at farm level in response to climate change on statistically influential factors. As can be seen in table 6 below Wald test in the header is highly significant, indicating a good model fit.

Climatic variables

Farm households are believed to practice different adaptation mechanisms in response long term changes in mean temperature and mean rainfall. Therefore, these climatic variables are expected to be the major determinants of the adoption of AWM. As expected the relationship between both mean temperature and mean rainfall with AWM adoption have found non-linear. The coefficient on mean temperature is found positive indicating that the increase in mean temperature leads farm households to adopt AWM. As it is shown in table 6 below a 1 degree Celsius rise in mean monthly

[13] Note: The three tables below are parts of one regression result and reported separately to simplify presentation.

temperature results a 34 percent increment of the likelihood of adopting AWM. However, such relationship ends after a while and this is shown by the non-linear relationship. The rise in mean temperature increases the probability of adopting AWM until mean temperature reaches 19.05 degree Celsius. After that point (19.05 degree Celsius) escalation of mean temperature level results a decrease in the probability of adopting AWM. The rise in mean temperature will first lead farm households to adopt agricultural technologies, related with water as there is moisture stress. However, the increase in mean temperature over and over will totally discard the existence of agricultural water and hinder farmers in adopting AWM practices.

A non- linear relationship is also found between mean rainfall level and adoption of AWM. The relationship between mean rainfall and AWM adoption is found negative implying that the existence of high level of mean rainfall results a decline in the prospect of adopting AWM. This may be due to the fact that the presence of abundant level of rainfall reduces the problem of agricultural water so that farm households will not be initiated to exert their effort on practicing AWM such as irrigation. Yet, such relationship between mean rainfall and AWM adoption wears out after a certain mean rainfall. Therefore, even if the rise in mean rainfall reduce the likelihood of practicing AWM, the availability of much level of mean rainfall have the reverse effect. Farmers with much level of rainfall will conserve their plots such as from floods by building terraces and will also drain the water using AWM practices.

Household characteristics

Various studies have shown that gender is an important variable affecting adoption decisions at the farm level. In this study gender is found insignificant in affecting the adoption decision of AWM. Likewise marital status of farm household head is also found insignificant in its effect on AWM adoption.

Although, literacy is expected to be a significant factor for adoption of AWM in our empirical finding it is found insignificant. Barret *et al* (2004) found education a positive significant factor of adoption. They argued that educated farm household heads, who are the primary decision makers, are more likely to adopt AWM than those who are not educated. Compared with the uneducated ones as a household is educated, he/she is likely to be more informed about the benefits of modern technologies and may have a greater ability of understanding about it. Not only the benefits of adopting but also the danger of not adopting is expected to be recognized easily by educated farm heads.

Age of the head of the farm household is statistically significant at 1 percent significance level and results indicate that an additional year to the age of the household head is associated with less probability of that household to adopt AWM. First, this may be because younger smallholder farmers are energetic than elder ones and agricultural technology adoption is labor intensive and older farm heads could lack the labor power required for AWM adoption purpose. Second compared with younger household heads older household heads would be less likely to adopt agricultural technologies such as AWM because they would believe that conventional ways of farming are still the best. The positive coefficient on squared age indicate a non-linear relationship between age of the farm household head and adoption of AWM.

Employment of a farm household member in non-farm business is found insignificant factor in determining AWM adoption. The coefficient on this variable is negative and it is possible to justify such inverse relationship. As household members participate in non-farm business their concentration to agricultural activities will decline. This is to say that a business out of agriculture competes the time for agricultural activities such as adopting agricultural water management and hence the probability of adopting agricultural technologies such as AWM in response to long term climate change will be low. Such negative relationship between adoption and off farm employment is found in the study by (McNamara et al 1991).

Another variable incorporated in the estimation is remittance obtained from relatives or friends by farm households. We found that remittance is a significant determinant of adoption of AWM and the relationship is found positive. A remittance obtained from relatives or friends can reduce the problem of liquidity required for the fulfillment of different instruments used to adopt AWM and this makes adoption simple.

Plot characteristics:

As many literatures our study incorporates plot characteristics including fertility, slope, altitude and shock index. From these factors altitude is found insignificant with a positive coefficient while fertility, slope and shock index are found significant with the expected sign. Fertility index is a significant factor of AWM adoption with a positive coefficient. This implies the higher the fertility index the higher the likelihood of adopting AWM. Hence in average farm households adopt AWM on their plots which are fertile than infertile. This may be due to as AWM adoption is costly farmers do not want to take risk by adopting it on infertile plots which are expected to be less productive than fertile plots. Slope index is also found significant and negatively related with adoption of AWM as the prior expectation. This indicates in average farm households adopted AWM on their plots which are flatter than the steeper ones. As plots become steeper and steeper it may be difficult to practice AWM. That means farmers may found AWM can easily be practiced on flatter plots compared with plots which are steep. Shock index is found as a positive significant factor of agricultural water management and its implication is that farm households who have faced agricultural shocks on their plot in the past adopted agricultural water management in a higher probability than who did not face such shocks.

Table 6 Climatic factors, and household and plot characteristics

Model	OLS		Endogenous Switching Regression					
	F(44, 4153)=237.29 Prob > F=0.000 R-squared=0.663 Root MSE=1.0559		Wald chi2(43) =1614.05 Log pseudo likelihood=-7251.3633		Prob > chi2 =0.000			
Dependent variable	Risk exposure for Pooled Data		Adoption Of AWM		Risk exposure For Adopters Of AWM		Risk exposure For non-adopters Of AWM	
	Column 1		Column 2		Column 3		Column 4	
Explanatory variables	Coefficient	Robust Std.Err.	Coefficient	Robust Std.Err.	Coefficient	Robust Std.Err.	Coefficient	Robust Std.Err.
AWM	.717***	(0.069)						
Climatic factors								
Mean temperature	0.564***	(0.038)	0.343***	(0.051)	0.279***	(0.044)	0.804***	(0.073)
Squared mean temperature	-0.016***	(0.002)	-0.009***	(0.003)	-0.007***	(0.002)	-0.021***	(0.003)
Mean rainfall	0.370***	(0.040)	-0.509***	(0.054)	0.410***	(0.050)	0.522***	(0.087)
Squared mean rainfall	-0.001	(0.001)	0.001	(0.001)	-0.001	(0.001)	-0.002	(0.002)
Household characteristics								
Marital status	0.009	(0.063)	0.045	(0.099)	0.122	(0.098)	-0.026	(0.074)
Gender	-0.008	(0.071)	-0.069	(0.119)	-0.113	(0.110)	0.035	(0.084)
Literacy	0.072**	(0.036)	0.044	(0.064)	0.230***	(0.055)	-0.068	(0.046)
Off farm activity	-0.042	(0.036)	-0.083	(0.064)	0.037	(0.055)	-0.026	(0.043)
Age	0.012	(0.009)	-0.080***	(0.017)	0.024**	(0.012)	0.009	(0.012)
Squared age	-0.0001	(0.0001)	0.001***	(0.00001)	-0.0002*	(0.0001)	-0.0001	(0.0001)
Remittance	-0.219***	(0.072)	0.188**	(0.091)	-0.022	(0.076)	-0.475***	(0.123)
Plot characteristics								
Fertility index	1.303***	(0.236)	2.245***	(0.310)	2.568**	(1.056)	0.662*	(0.347)
Slope index	-0.117	(0.129)	-0.546***	(0.195)	-0.169	(0.202)	-0.050	(0.158)
Altitude	-0.163	(0.323)	0.077	(0.422)	-0.558	(0.429)	-0.082	(0.361)
Shock index	0.223	(0.140)	0.725***	(0.227)	0.134	(0.210)	0.147	(0.206)
Sample size	4198		4198		1617		2581	

Note: Estimation by OLS (first column) and full information maximum likelihood for the remaining columns at the plot-level with zonal dummy, robust standard errors in parenthesis. Sample size: 4198 plots. ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level.

Regression results of assets, input, institutional factors and crop dummy are presented in table 7 below.

Assets:

In these study the value of productive farm asset, farming land (farm size), and tropical livestock unit are considered as assets of farm households which will have an effect on the adoption of agricultural water management. The result shows that the effect of value productive farm asset and farm size on adoption of AWM is insignificant where the coefficient on these variables are found negative.

Ownership of livestock in tropical livestock unit is also found a negative significant factor of AWM adoption so that farmers with large TLU opt to not adopt AWM and this may be due to farmers with large TLU concentrate on livestock raring rather than crop production.

Institutional Factors

Access to credit, agricultural information from different sources, access to information on climate by extension workers, cooperative membership, and land certification are the institutional factors which are frequently considered in adoption literature. Likewise, these variables are included in our study and most of them are found significant factors for the adoption of AWM.

Access to credit is found a positive significant factor of the adoption of agricultural water management as expected. The reason behind such result may be the issue of liquidity. That means farmers with credit access can reduce their shortage of cash in need of the purchase of inputs for adoption purpose than those who are credit constrained. This result is aligned with most of the studies in this area such as (Caviglia-Harris 2002; Saín and Barreto 1996).

The adoption of agricultural water management is also found to be positively affected by cooperative membership of a farm household. That is farmers who are members of agricultural cooperatives are more likely to take up adaptation mechanisms which is agricultural water management in our case. This outcome is supported by the study (Uwagboe *et al*, 2012) where farmers' who are a member of such groups have higher likelihood of agricultural technology adoption and high level of crop production.

Farmers were also asked whether the sampled plots are certified or not and we inter this as one of the institutional variables which are expected to determine AWM. We found that the effect of land certification on AWM is significant with a positive coefficient. Farm households will practice different strategies to minimize downside risk exposure such as AWM if their plots are certified as there is a sense of ownership compared with plots which are not certified. A result consistent with this is found by (Teklewold *et al*, 2013) where a positive relationship between sense of land ownership and agricultural performance of farmers was demonstrated.

Crop groups

The adoption of agricultural technology is expected to have a relative benefit for one crop type than the other crop type. Similarly agricultural water management is not expected to have similar relevance for all crops which are planted in the study area. In our study we classified the planted crops in to three groups which are cereal, pulse and Vegetables and fruits[14]. Vegetables and fruits are bases of the crop dummy so that cereal and pulse are included in our regression. The result shows that the relationship between both cereal and pulse with AWM is negative relative with the base dummy even if it is found insignificant. This indicates that agricultural water management is applied for Vegetables and fruits than cereals as well as pulses. Most of the time Vegetables and fruits are planted in areas where agricultural water management technologies such as irrigation and ponds are available compared with cereal and pulses. This is due to the fact that Vegetables

[14] Note: In this study vegetables and fruits are grouped in one category.

and fruits are more water intensive than the respective cereals and pulses. Besides, Vegetables and fruits have higher market prices than cereals and pulses. The existence of high market price for Vegetables and fruits can prompt the adoption of AWM.

Table 7 Assets, input, institutional factors and crop dummy

Model	OLS		Endogenous Switching Regression					
Dependent variable	Risk exposure for Pooled Data		Adoption Of AWM		Risk exposure For Adopters Of AWM		Risk exposure For non-adopters Of AWM	
	Column 1		Column 2		Column 3		Column 4	
	Coefficient	Robust Std.Err.	Coefficient	Robust Std.Err.	Coefficient	Robust Std.Err.	Coefficient	Robust Std.Err.
Explanatory variables								
Assets								
Value of productive farm asset	-0.137*	(0.070)	-0.046	(0.106)	-0.077	(0.098)	-0.159*	(0.088)
Tropical livestock unit	-0.008	(0.006)	-0.022**	(0.010)	-0.012	(0.009)	0.006	(0.008)
Farm size	0.023	(0.017)	-0.036	(0.028)	-0.010	(0.031)	0.037**	(0.018)
Institutional factors								
Land certification	-0.009	(0.041)	0.222**	(0.089)	-0.109	(0.076)	0.003	(0.045)
Credit access	0.091	(0.061)	1.315***	(0.114)	0.312*	(0.161)	0.155	(0.098)
Cooperative membership	0.324***	(0.053)	1.378***	(0.078)	1.190***	(0.233)	0.030	(0.110)
Input								
Organic fertilizer	-2.373	(2.695)			-11.213***	(3.523)	0.693	(3.543)
Squared Organic fertilizer	0.0005	(0.0003)			0.001***	(0.0004)	0.0001	(0.0004)
Crop dummy								
Cereal dummy	-0.481***	(0.086)	-0.013	(0.113)	-0.314***	(0.116)	-0.498***	(0.109)
Pulse dummy	-0.518***	(0.098)	-0.015	(0.128)	-0.203	(0.127)	-0.589***	(0.124)
Sample size	4198		4198		1617		2581	

Note: Estimation by OLS (first column) and full information maximum likelihood for the remaining columns at the plot-level with zonal dummy, robust standard errors in parenthesis. Sample size: 4198 plots. ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level:

Selection instruments

Table 8 below depicts the regression results of selection instruments and other important tests.

Household size[15] (labor supply) is found a positive significant factor of AWM. This is not surprising because adoption of AWM is labor intensive practice. This problem can be minimized if a farm household have more active household members than those with a small number. A study by Mauriceet al (2009) found a consistent result with this.

Climate information and agricultural information from different sources (government extension, media and neighbor) are taken as explanatory variables of adoption of AWM. Except information from media (which is found insignificant with the expected sign) all of these variables affect adoption of AWM positively and significantly. This is may be due to the fact that information access enhances the efficiency of decision making regarding adoption. This suggests that extension services help farmers to take climate changes and weather patterns into account and help advise them on how to tackle climatic variability and change. Thus information plays a significant role at influencing smallholder farm households to adopt AWM and those households that face information asymmetry would less likely adopt AWM. The result has the same implication with studies by Wozniak (1984) and Adesina and Forson (1995), where both of these studies indicate agricultural extension is important for adopting agricultural technologies. The result is also consistent with the findings of Koundouri et al (2006) where a study was conducted on irrigation technology adoption under production uncertainty and confirmed that farm households that have informed are more likely to adopt new technologies than other farmers.

[15] Note: Household size, climate forecast information, information from different sources (media, neighbor and government extension) and market access are our selection instruments. That is these variables are incorporated only in the selection equation and not in the outcome equation.

Another instrumental variable used in our study here is market access. We have taken the time which takes to the nearest market by which farmers are used in order to purchase inputs and sold their agricultural outputs. We found this variable significant determinant of AWM with negative sign. Farmers who are far from markets will not have the access to purchase the inputs or the machineries of adoption. In addition farmers who are far from town cannot have the information obtained from extension officers who were based in cities. A result in line with this was found in the study by (Wollni et al, 2010).

The Wald test for joint independence of the three equations is reported in the last line of the output (reported at table 8) and it is found significant. Thus encouraging the usefulness of adding the IMR (inverse mills ratio) in our regression. This further guaranteed the validity of using endogenous switching regression model.

The correlation coefficient for adopters of AWM (ρ_1) is negative and significantly different from zero at 1 percent level indicating that the null hypothesis of sample selection is not rejected. This suggests that farm households that choose to adopt AWM have obtained higher income skewness per hectare (i.e. a reduction in downside risk exposure) due to unobserved characteristics than a random smallholder farm household from the sample, would have obtained.

On the other hand, the correlation coefficient for non-adopters (ρ_2) is positive but not significantly different from zero. Even if it could not have been known priori, the implication of this result is the null hypothesis of absence of sample selectivity bias cannot be rejected (Di Falco et al, 2011).This suggests that farm households who did not adopt AWM obtain neither higher nor lower reduction in downside risk exposure than a random farm household in the sample.

Table 8 Selection instruments and Joint tests

Model	OLS		Endogenous Switching Regression					
Dependent variable	Risk exposure for Pooled Data		Adoption Of AWM		Risk exposure For Adopters Of AWM		Risk exposure For non-adopters Of AWM	
	Column 1		Column 2		Column 3		Column 4	
	Coefficient	Robust Std.Err.	Coefficient	Robust Std.Err.	Coefficient	Robust Std.Err.	Coefficient	Robust Std.Err.
Explanatory variables								
Selection instruments								
Climate information			1.106***	(0.097)				
Media information			0.092	(0.123)				
Extension information			0.753***	(0.098)				
Neighbor information			0.607***	(0.130)				
Market access			-0.003***	(0.001)				
Household size			0.138***	(0.016)				
Constant	-4.874***	(0.678)	-5.947***	(1.093)	-3.637***	(1.330)	-6.635***	(0.919)
σ_i					0.947	(0.047)	1.007	(0.067)
ρ_i					-0.179***	(0.044)	0.166	(0.206)
Joint tests								
JTZ(F-test)	13.14***		180.35***(χ^2)		12.79***		7.28***	
JTMF(F-test)	2.63**		3.91(χ^2)		1.43		0.97	
JTI(χ^2, F-test)			274.18***(χ^2)				1.86*	
WTIE(χ^2)			17.36***					
Sample size	4198		4198		1617		2581	

Note: Estimation by OLS (first column) and full information maximum likelihood for the remaining columns at the plot-level with zonal dummy, robust standard errors in parenthesis. Sample size: 4198 plots. ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level: JTZ= joint significance test on zones, JTMF=joint test on Mundlak's fixed effects, JTI= joint test on selection instruments, WTIE= Wald test of independent equations.

4.2.2.2. Determinants of Downside Risk Exposure

As one of our objective is to compare the downside risk exposure of farm households who adopted AWM and who did not adopt determining the skewness of the farm income function in order to measure the downside risk exposure of farm households is required. This helps as to answer the question of whether farm households benefited or not from adoption of AWM.

To control for unobservable plot characteristics we include Mundlak's fixed effects in our estimates of the skewness functions. The consideration of fixed effects is very important in this setting as these effects would remove plot invariant characteristics such as skills and motivation. We test for the relevance of the fixed effects with OLS, and we reject the null hypothesis that they are jointly equal to zero only for the pooled sample at 1 percent statistical level. However the null hypothesis of the zero joint significance of fixed effects do not be rejected for the selection equation (adoption), and risk function of group of adopters and group non-adopters.

Variation between the sample zones was expected and in this study location dummies are included in order to the see whether the difference in zones are jointly significant in determining our dependent variables or not. As shown in table 8 above the joint significance of the dissimilarity of zones in determining dependent variables is found highly significant in all cases. This implies, the variation in zones resulted in a difference for the dependent variables in the study area.

In order to avoid the identifiability problem selection instruments are taken. We took market access, household size, climate information, and agricultural information from different sources as selection instruments of our study. These variables are expected to have a direct effect on the dependent variable of the selection equation, that is AWM but these variables expected to not have a direct effect on dependent variable of the continuous equation that is risk exposure. For instance the existence of large number of household size will have a direct effect on AWM adoption as it indicates the availability of labor power. However, having large or small number of family members have not a direct relationship with risk exposure of farm households.

The validity of these instruments is assured using two tests. In the first place selection instruments should be jointly significant in determining the dependent variable in the selection model. The robust probit regression result shows that the effect of instruments on AWM (i.e. the dependent variable in the selection equation) is jointly significant at one percent level of significance (χ^2=274.18***). However this is the first step in testing the validity of selection instruments. In the second step selection instruments should as much as possible be jointly insignificant in their effect on the dependent variable of the outcome equation of those who did not adopt AWM. Therefore the effect of the selection instruments on the third central moment of the farm income function of non-adopters should be jointly negligible. A simple OLS regression is conducted on skewness of the farm income function of non-adopters having the selection instruments and other explanatory variables. The result illustrates that the joint effect of selection instruments on non-adopters skewness function is trivial compared with the effect on the selection equation (F-stat. = 1.86).

As we can see in the first columns of Tables 6, 7, and 8 above we estimate the skewness function for the whole sample using OLS estimation technique having AWM an explanatory variable. The result shows that adoption of AWM has a positive effect on the skewness function (i.e. reduces downside risk exposure) of the farm income and it is highly significant (statistically significant at 1 percent). OLS results in column (1) of table 6 indicate that holding other covariates constant, smallholder farm households who adopted AWM would have 71 percent higher skewness than their counterparts who did not adopt it and the coefficient for adoption is highly significant. That is farm households who adopted AWM have a 71 percent more likelihood of reducing downside risk exposure.

Yet, in this regression adoption of AWM is assumed as strictly exogenous while it is a deliberate decision and thus it is potentially endogenous. Such estimation will lead to biased estimates since adoption is considered as exogenous while it is endogenous. This is to mean that the results from it would be biased and inconsistent as it would not account for endogenous switching for adoption of AWM. Moreover, estimating skewness by OLS in order to measure downside risk exposure cannot help as to identify the structural differences of downside risk exposure between adopters and non- adopters of AWM.

In the last two columns of the tables 6, 7, and 8 above the regression results of determinants of skewness by employing the endogenous switching regression for adopters and non- adopters of AWM are presented. Climatic factors, crop dummy, and fertility index of the farm household are found the key drivers of the skewness function of the income for both adopters and non-adopters of the AWM practice.

As it is said in the previous section the correlation coefficient is found significant for adopters and insignificant for the non-adopters. This implies in addition to the sample selection bias the differences in the coefficients of the skewness functions between the farm households that adopted and those who did not adopt illustrate the presence of slope heterogeneity in the sample. That is there are factors which affect the two groups (i.e. adopters and non-adopters of AWM) differently. The risk function of farm households those who adopt AWM is significantly different from the risk function of farm households who did not adopt (at the 1 percent statistical level, F-stat. = 2189.144)[16].

[16]Note: F-stat. to identify the existence of difference in coefficients of risk exposure for adopters and non-adopters is computed after OLS regression is conducted on the total sample, adopters, and non-adopters separately using the

Climatic factors

As in the case of adoption of AWM the effect of mean temperature and rainfall on downside risk exposure is expected to be nonlinear and to consider such nonlinear effect, the squared-term of rainfall and mean temperature are included in our model. In line with the expectation the results show that mean rainfall and mean temperature have a non-linear effect on downside risk exposure. Both mean rainfall and mean temperature are found significant factors in affecting risk exposure for adopters and non-adopters of AWM.

As it can be seen from Table 6 above the increase in mean temperature results in a reduction in downside risk exposure for adopters as well as for the non-adopters of AWM. Moreover, the coefficient of mean temperature is higher for the non-adopters (0.804) when we compare it with the adopters (0.279). From this result it seems that the effect of mean temperature on reducing downside risk exposure is higher for the non-adopters of AWM associated to the adopters which makes non-adopters of AWM more resilient for the increment of mean temperature than the adopters. However, the reverse is found when we compute the optimal point of mean temperature for adopters and non-adopters of AWM on which downside risk exposure starts to rise due to the rise in mean temperature. Considering not only mean temperature but also its squared term and calculating its effect on downside risk exposure (i.e. taking the first order derivative of risk function with respect to mean temperature) of adopters and non-adopters it is found that adopters

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formula in chow test. That is F(K, $(N_{1+}N_2 - 2K)$)=$\frac{[(essc-(ess1+ess2))/K]}{[(ess1+ess2/(N_{1+}N_2-2K)]}$, where K =number of parameters estimated, N_1 = number of observation in the first group of regression(adopters), N_2=number of observation in the second group of regression(non-adopters), $essc$ =explained sum of square for the combined regression (adopters and non-adopters), $ess1$ =explained sum of square for the first regression (adopters), and $ess2$ =explained sum of square for the second regression (non-adopters).

were more resilient to the increase in mean temperature than the non-adopters. Initially, the rise in temperature reduces the downside risk exposure of farm households who adopted and who did not adopt AWM. But downside risk exposure of the non-adopters started to rise at lower mean temperature (19.6 degree Celsius) than adopters (20 degree Celsius). This implies that given other things constant, adoption of AWM can help farm households to reduce the likelihood of exposing to crop failure due to the rise in mean temperature.

Like that of mean temperature the escalation in mean rainfall results in a reduction in downside risk exposure of farm households for adopters and non-adopters as well. Also the coefficient of this variable is higher for the adopters (0.522) than the non-adopters (0.410) which simply implies the effect of mean rainfall on downside risk exposure is higher for adopters than the non-adopters of AWM. Moreover, as in the previous case if we see the point where the linear relationship between mean rainfall and downside risk exposure ends a consistent result is found. The first order derivative of the risk function with respect to mean rainfall shows that the linear relationship wears at a higher level of mean rainfall for adopters than for non-adopters of AWM. This implies adopters of AWM were more resilient to the increase in mean rainfall level than those who did not adopt AWM and this in turn indicates AWM is among the mechanisms which run to minimize downside risk exposure.

All in all, the rise in mean temperature or rainfall results a decrease in downside risk up to a certain amount and after a certain extent the effect of these variables diverted to negative. Therefore up to the point where the linear relationship between these climatic variables and downside risk break up mean rainfall or mean temperature are helpful to minimize farm households' downside risk exposure. However, much amount of mean rainfall and mean temperature negatively affect skewness so that it leads farmers to face production risk. For instance, much rainfall will result in flood and this in turn lead to crop failure. Besides, the effect of these variables is not identical for farm households who adopted and did not adopt AWM. The result shows that adopters of AWM were more resilient for extreme maximum values of these factors.

Household characteristics

Literacy is also found a positive significant factor for reducing downside risk exposure of adopters of AWM. That is, among farm households who adopted AWM the probability of downside risk exposure (e.g. crop failure) is lower for those who are educated compared with illiterates. As we can see from Table 6 above being educated results in a reduction of downside risk exposure by around 23 percent for adopters of AWM. Unfortunately, the coefficient on education is found negative in reducing downside risk exposure of farmers who did not adopted AWM even if the effect is found negligible.

Surprisingly, remittance which have a significant positive effect on the adoption of AWM is found negative determinant of downside risk exposure for both adopter and non-adopters of AWM and statistically insignificant for adopters. The negative effect of remittance on skewness may be due to the dependency problem that will happen on farm households and this may in turn lead farmers to have lower concentration on their agricultural activities as there is an expected income to be sent from relatives. That means for adopters agricultural activities other than AWM will be left by those who have had remittance. Moreover, those who did not adopt AWM having remittance will have a very low level of skewness at the beginning (high probability of downside risk exposure) and this can make the relationship negative.

Marital status, gender, and off farm business are the factors which are found insignificant in determining downside risk exposure of farm households that adopted as well as who did not adopt

AWM. Among this factors marital status and off farm business are found with positive and negative coefficients on adopters and non-adopters accordingly. On the other hand, gender is found positive in reducing downside risk exposure of non-adopters while it is negative for adopters. Regarding age a significant positive relationship between reduction in downside risk exposure and age level is found for the group of adopters while it is positive and insignificant for the non-adopters. The negative coefficient on age square indicates a non-linear effect of age on downside risk exposure.

Crop group

Another interesting result is, compared with the category of Vegetables and fruits the skewness of cereals and pulses is found lower although pulse dummy is insignificant for adopters. That means downside risk exposure is found higher for cereal groups as well as pulse groups associated with Vegetables and fruits group. Linked with the group of vegetable and fruits those farmers (adopters and non-adopters) who have grown cereals exposed to downside risk exposure by more than around 31 and 50 percent respectively. Likewise, non-adopter farm households who have grown pulse exposed to downside risk exposure by 59 percent more than those who have harvested vegetable and fruits. In our explanation of the determinants of AWM we have found that AWM is adopted in vegetable and fruit crop group than other crop category. Further, we know that AWM practices are risk decreasing practices and our empirical finding on skewness regarding crop group is consistent with this argument.

Institutional characteristics

Cooperative membership is found a positive significant factor for reducing downside risk exposure of adopters so that farm households who were members of agricultural cooperation run to minimize the probability of downside risk exposure compared with those who were not members. Given other things unchanged, being a member of agricultural cooperation can ease the availability of different inputs used for production as well as adoption purpose. In addition becoming a member of cooperation can help farm households in accessing information regarding climate and other agricultural techniques. Having this farmers who were part of cooperatives can hedge themselves against production risk than those who were not members.

Credit is another variable which is found positive and significant factor of skewness of adopters of AWM. As argued previously, farmers who have access to credit can curtail the problem of liquidity and therefore they can easily mobilize resources used for production. If the problem of liquidity is not there they can even grow crops which are more resilient than those which are venerable to the change in climate. Hence, farmers who have credit access can reduced their downside risk exposure or crop failure associated with those who were credit constrained. Being a member of agricultural cooperation and having credit access the group of adopters can reduce downside risk exposure by 110 and 32 percent respectively. Incredibly, for the group adopters the coefficient on land certification is found negative even if it is insignificant. For the group of non-adopters all these institutional factors are found insignificant, but the sign of the coefficients bring into being as expected.

Assets:

All asset variables incorporated in this study (i.e. livestock in tropical livestock unit, farm size and value of productive farm asset) are found insignificant in determining downside risk exposure of farm households who adopted AWM. Moreover, the coefficients on all these variables are found negative. For the group of non-adopters except value of productive farm asset (which is found significant with negative coefficient) the two variables positively affect skewness of income, that is contribute to the reduction in downside risk of farm households. But tropical livestock unit is statistically insignificant. Income skewness of farm households with relatively high level of value of productive farm asset may be lower at the beginning which makes the coefficient of the variable negative.

Organic fertilizer is the other variable which is expected to affect the downside risk exposure of farm households through skewness of income. This variable is found negative significant factor in reducing downside risk exposure of the adopters of AWM and insignificant for the non-adopters. The negative coefficient on organic fertilizer may be due to the fact that those who used organic fertilizer may not use other inputs such as in organic fertilizer. In addition, the effect of organic fertilizer is not seen in the short run. The positive sign on the square tem of organic fertilizer for the adopters sub sample indicate a non- linear effect of this variable on downside risk exposure.

Plot characteristics

Like the result we found in the adoption of AWM most of the plot characteristics are found insignificant in determining downside risk exposure of farm households. The estimated coefficient for fertility index is positive for both groups (adopters and non-adopters) as expected which implies fertile plots are associated with a decrease in downside risk exposure and the reverse is true for infertile plots.

4.2.3. Average Expected Downside Risk Exposure

From our previous discussion we found that adoption of AWM have a positive significant effect in reducing downside risk exposure of farm households. This simple evaluation is misleading as observed and unobserved elements which may have an effect on the outcome variable were not considered. Therefore, the outcome variable (risk exposure) of farm households who adopted

AWM are compared with what they would have been if the farm households had not adopted. This helps us to come up with the true estimate of average adoption effect for households that did adopt AWM.

In order to determine the average adoption effects of AWM under the actual and counterfactual circumstances, the result on the expected downside risk exposure is presented in Table 6. The result suggests adoption of AWM have not the same effects on those who did not adopt if they choose to adopt as it would on adopters.

Our estimation results show that AWM adoption significantly increases farm income skewness. Therefore, adoption of AWM reduces the exposure of farm households to downside risk and so the probability of crop failure. Di Falco et al (2012) also found a consistent result by which adaptation with a set of strategies to climate change reduces farmers' exposure to production risk.

Adoption effect of AWM is determined for farm households who adopted AWM and who did not adopt by taking the respective counterfactual conditions. The number in the first cell of Table 9 (2.118) is the average farm income skewness of farm households that adopted AWM. This is the average farm income skewness for those who adopted AWM in the actual condition. The number in the second cell (1.448) indicates the counterfactual average farm income skewness of those who adopted AWM. This is the average farm income skewness of farm households who adopted AWM if they did not adopt it. Subtracting the second from the first we found the adoption effect for the adopters. This is positive and significantly different from zero (0.670***). The result suggests that income skewness for those farm households who adopted AWM will significantly higher than if they did not adopted AWM. In similarly words, downside risk exposure of farm households who adopted AWM is lower than what actually is if they did not adopt. As a result, AWM adoption is advantageous in helping farmers to hedge against the risk of production failure by improving their resilient capacity to extreme climatic conditions.

From the same table the adoption effect for farm households who did not adopt AWM is computed with the same procedure. The counterfactual average skewness (i.e. average skewness of non-adopters if they had adopted) is the first number in the second row of the Table (2.685). The second number of this row (1.925) is the actual average skewness of farm income for the non-adopters of AWM. Deducting the second from the first a result which is positive and significantly different from zero (0.759***) is found. The result shows that farm households who did not adopt AWM can have a higher average skewness of income than what actually have if they had adopted it. By the same token, downside risk exposure of non- adopter farm households will be lower than what actually is if they had adopted AWM.

The existence of potential heterogeneity effects between the adopters and non-adopters of AWM is adjusted in the last row of Table 9. If non-adopters of AWM had decided to adopt AWM, they would be expected to have realized higher skewness of income per hectare than the adopters. This implies that smallholder farm households that did not adopt AWM would be better off compared to adopters of the AWM in terms of downside risk reduction, perhaps new adopters would have to get established in order to have similar returns as their counterparts. Furthermore, Column (2) of the last row shows that if adopters of AWM had decided not to adopt it, they would still be expected to realize lower skewness of income than non-adopters. Therefore, if adopters had decided not to adopt their risk exposure would have been higher than that of the non-adopters. Generally, under similar scenarios (i.e. both being adopters and both being non-adopters) farm households who did not adopted AWM are less exposed to downside risk than the adopters.

Lastly, transitional heterogeneity effects are found by subtracting the adoption effect of non-adopters from the adoption effect of adopters (-0.089***). This implies that, non-adopters of AWM are expected to have more income skewness per hectare so that a higher reduction in downside risk, the reason being that there are important sources of heterogeneity (for example farming skills) within them that enable them realize more income skewness per hectare than their counterparts.

Table 9 Adoption and heterogeneity effects of AWM

		Decision stage		Adoption effects
		Adoption	Non-adoption	
Sub samples	Adopters	I. 2.118 (0.043)	II.1.448 (0.031)	TT= 0.670*** (0.053)
	Non-adopters	III. 2.685 (0.036)	IV. 1.925 (0.026)	TU=0.759*** (0.045)
	Heterogeneity effects	BH1= -0.567*** (0.056)	BH2= -0.477*** (0.040)	TH=-0.089*** (0.021)

Note: TT=Adoption effect for adopters, TU= Adoption effect for non-adopters, BH=Base heterogeneity, TH=Transitional heterogeneity (TT-TU). ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level: (I) $= E(y_{1i}/P_i = 1)$, (II) $= E(y_{2i}/P_i = 1)$, (III) $= E(y_{1i}/P_i = 0)$, and (IV)$= E(y_{2i}/P_i = 0)$,WhereP_i= 1 if farm households adopted AWM to climate change; P_i= 0 if farm households did not adopt AWM; y_{1i} and y_{2i} are the third central moment $f_3(R, \beta_3)$ of the income function if farm households adopted and did not adopt AWM accordingly.

CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

The general objective of this study is to examine the contribution of agricultural water management practices in reducing household's downside risk exposure. Specifically factors of AWM adoption and downside risk exposure are determined. Investigating the differences in downside risk exposure of farm households who adopted and did not adopt AWM both in actual and counterfactual scenarios were also the aims of this study. To achieve these objectives, the study used the 2015 survey databases on 929 farm households collected in the Nile basin of Ethiopia by ECRC/EDRI. Our final data is composed of 821 farm households and 4198 plots. Moreover, endogenous switching regression methodology is employed for the study. Through this method, a simultaneous equations model with endogenous switching which account for unobservable factors that influence downside risk exposure of farm households and the decision to adopt AWM was used to estimate the effect.

From the results of the study the following main conclusions could be drawn. First climatic variables, institutional factors and information are the major determinants of farm households AWM adoption. Both mean temperature and mean rainfall are found in a non-linear relationship with adoption where the increase in mean temperature increase the likelihood of adopting AWM and the reverse is true for the increase in mean rainfall. Credit availability and cooperative membership are the key institutional factors which enhances the likelihood of adoption of AWM. Moreover climate information and any agricultural information provided from different sources are found important activators of AWM adoption. Household size and market access are also the factors which influence farm households' adoption of AWM. Even if crop group dummies are found insignificant in determining adoption the sign on the coefficients imply that AWM was adopted more on vegetable and fruits than cereals and pulses. This can be due to the level of price tagged for Vegetables and fruits is relatively higher than that of cereals as well as pulses.

Second, AWM is found to be adopted in highly fertile and flatter plots than infertile and steep plots. The risk averse nature of farm households can make them to adopt costly practices such AWM in fertile plots which are expected to bring higher returns in normal situations than in infertile plots. A steepness in plots can make the adoption of AWM such as irrigation difficult to practice and this may be the reason for the negative coefficient on slope index in affecting adoption of AWM. Furthermore, farm households are found with a higher probability of AWM adoption if the shock index is higher. This indicates that, the likelihood of adopting AWM is higher for farm households who faced more shocks in the past as they fear and run to hedge themselves from the past shocks.

Third, as in the case of adoption climatic variables and institutional factors are the major determinants of downside risk exposure of farm households who adopted as well as who did not adopt AWM. The rise in mean rainfall and mean temperature up to a certain point is found essential in reducing downside risk exposure of farm households while this relationship wears after an optimal point for both variables in the two regimes. Even if the relationship of these climate factors with a reduction in downside risk exposure of adopters and non-adopters is found similar the optimal point by which the relationship turns to negative from positive is higher for the adopters than the non-adopters. The implication of this result is farm households who adopted AWM are more resilient to the higher extreme values of mean temperature and mean rainfall than those who did not adopt it. Access to credit and cooperative membership and literacy are factors which are found positive and significant for downside risk reduction. Land certification is found with positive coefficient while it is significant only for the non-adopters.

Fourth, Regarding crop grown, vegetable and fruits are found important in reducing downside risk exposure of both adopters and non-adopters compared with cereal groups and pulse groups. This may be due to the fact that Vegetables and fruits have attractive (higher) prices than cereals and pulses as they are more of high value crops. Therefore, small holder farmers are expected to invest costly adaptation mechanisms such as AWM on plots grown vegetable and fruits than cereals and pulses. This in turn minimizes farmer's exposure to downside risk.

Fifth, both adopters and non-adopters of AWM would realize higher income skewness (i.e. a reduction in downside risk exposure) had both decided to adopt AWM than they would if they had not adopted it. Compared with the adopters non-adopters of AWM would be better off if they adopted AWM. That means non-adopters can realize a higher reduction in downside risk exposure than adopters if they decided to adopt AWM. Furthermore, non-adopters of AWM would be better than adopters if both groups of farmers decided not to adopt. Therefore, farm households that adopted AWM only realized a higher reduction in downside risk exposure when they decided to adopt, but with the same scenario, they would be worse off than non-adopters.

Sixth, there are some important sources of heterogeneity, such as skill between adopters and non-adopters of AWM. These heterogeneity between the two groups make the non-adopters less exposed to downside risk than the adopters. Such differences signify sources of variation between the two groups that estimation by OLS model including a dummy variable for adopting AWM or not to climate change cannot consider. More importantly, climate change adaptation through AWM is a successful risk management strategy that makes the adopters' more resilient to climatic conditions.

5.2. Recommendations

The findings of this study are particularly important to design policies for effective promotion of AWM technologies in order to enhance the livelihood of farm households in the Nile basin of Ethiopia. AWM adoption have to be encouraged through the positive results realized by farm households who adopted it. Hence this study draw the following policy implications:

- The diffusion of climate change information through different sources are found important factors which increase the likelihood of adopting AWM. Thus, more should be done by policy makers on disseminating information regarding climate change to farm households. This can create awareness on farmers about the negative consequences of climate change which in turn leads farmers to take up different adaptation mechanisms such as AWM which will prevent them from exposing to the downside risk exposure. Moreover, distance to market significantly determines the adoption of adaptation mechanisms which is AWM in our case. Therefore alternatives should be placed in accessing inputs used for adoption for farmers in areas where markets are far apart.
- Cooperative membership and credit access are the other variables which are found positive relationship in increasing the likelihood of adoption of AWM and so as to reduce downside risk exposure. Therefore, further activities should be done by the concerned body in order to improve credit access and agricultural cooperatives of farm households.
- As AWM plays an important role in reducing downside risk exposure (i.e. the probability of crop failure) the current agricultural extension program should consider on the wide adoption and diffusion of AWM techniques in order to minimize the likelihood of crop failure.

- Even if, the two groups (adopters and non-adopters) are found better off when they have adopted than the other way, the role of AWM adoption in reducing the probability of crop failure is not found the same for adopters and non-adopters of it. This implies the existence of heterogeneity between the two groups. Therefore, the existence of heterogeneity among farm households should be the concern of policy makers in the process of publicizing AWM in order to reap higher benefit from the practice.

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APPENDICES

A1: REGRESSION RESULTS OF INCOME FUNCTION

Endogenous switching regression model; Number of observations: 4198

Log pseudo likelihood=-41014.448 Wald chi2 (43) =5087.50 Prob > chi2=0.000

Dependent variable	Farm income for adopters of AWM	Farm income for Non-adopters of AWM
Explanatory variables		
Mean temperature	1777.632***	2442.767***
	(154.305)	(215.887)
Squared mean temperature	-19.320***	-85.008***
	(7.631)	(7.983)
Mean rainfall	375.028***	2258.365***
	(270.659)	(201.169)
Squared mean rainfall	-0.008***	-0.008***
	(0.002)	(0.002)
Marital status	1789.798	-132.279
	(332.030)	(213.568)
Gender	-1491.871	225.894
	(404.231)	(251.127)
Literacy	1133.469***	1715.942***
	(208.620)	(149.451)
Off farm activity	-474.140	-154.697
	(192.402)	(145.262)
Age	-62.538	-1.118
	(44.492)	(32.644)
Squared age	0.661	0.129
	(0.414)	(0.291)
Remittance	5571.340***	5585.601***
	(276.648)	(310.540)
Fertility index	9602.165***	4408.316***
	(2455.789)	(394.235)
Slope index	-3310.597***	-1349.572***
	(759.387)	(481.035)
Altitude	-312.6303	1102.524
	(1592.655)	(1079.91)
Shock index	-858.407***	-1576.691***
	(1002.916)	(568.221)
Value of productive farm asset	628.015*	888.931***
	(314.142)	(278.017)

Tropical livestock unit	97.449	37.790
	(30.352)	(23.832)
Farm size	-465.439***	-491.085***
	(97.008)	(63.285)
Land certification	444.392	-154.978
	(256.799)	(162.165)
Credit access	4656.503***	1003.782***
	(1246.422)	(228.501)
Cooperative membership	6875.628***	830.825***
	(811.466)	(165.570)
Organic fertilizer	78539.83***	-9785.665
	(15282.19)	(10223.99)
Squared Organic fertilizer	-10.435***	1.498
	(2.062)	(1.390)
Cereal dummy	-2170.571**	769.183**
	(392.063)	(330.162)
Pulse dummy	-2139.584***	1243.340***
	(407.572)	(369.602)
Mean organic fertilizer	-0.082*	0.119*
	(0.255)	(0.068)
Mean fertility index	1267.834***	-3774.024***
	(715.053)	(522.624)
Mean slope index	3397.101	1064.579
	(1021.543)	(730.032)
Mean shock index	-1319.671	398.849
	(839.114)	(698.614)
Mean altitude	0.289****	-3.143***
	(1.868)	(1.190)
East Tigray dummy	-4957.285***	3876.845***
	(1328.391)	(694.372)
South Tigray dummy	-2715.220***	6701.592***
	(1233.532)	(867.610)
Metekel dummy	-1439.514***	9840.789***
	(1686.384)	(1099.686)
North Gonder dummy	-524.517***	7646.709***
	(1166.008)	(700.814)
South Gonder dummy	2385.170***	2328.535***
	(647.849)	(423.538)
East Gojjam dummy	1348.825***	1523.398***
	(970.211)	(500.985)
West Gojjam dummy	7657.459***	5784.380***
	(974.296)	(511.305)
West Wellega dummy	6663.662***	5357.062***
	(1534.013)	(685.754)
East Wellega dummy	2912.494***	5849.148***
	(1892.457)	(798.802)

North Shoa dummy	6583.939***	4793.319***
	(1144.904)	(562.458)
Assosa dummy	1669.160***	11748.220***
	(2094.199)	(1409.296)
Kamshi dummy	14.613***	6238.099***
	(2172.107)	(1243.666)
Keffa dummy	-1292.587***	1990.869***
	(900.540)	(456.042)
Constant	-36295.610***	-13495.730***
	(5056.834)	(2731.994

Note: Estimation by full information maximum likelihood at the plot-level with zonal dummy, robust standard errors in parenthesis. Sample size: 4198 plots. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level

A2: REGRESSION RESULTS OF DOWNSIDE RISK EXPOSURE

Endogenous switching regression model; number of observations: 4198

Log pseudo likelihood=-7251.3633 Wald chi2 (43) =1614.05 Prob > chi2 =0.000

Dependent variable	Risk exposure for adopters of AWM	Risk exposure for non-adopters of AWM	Adoption of AWM 1/0
Explanatory variables			
Mean temperature	0.279***	0.804***	0.343***
	(0.044)	(0.073)	(0.051)
Squared mean temperature	-0.007***	-0.021***	-0.009***
	(0.002)	(0.003)	(0.003)
Mean rainfall	0.410***	0.522***	-0.509***
	(0.050)	(0.087)	(0.054)
Squared mean rainfall	-0.001	-0.002	0.001
	(0.001)	(0.002)	(0.001)
Marital status	0.122	-0.026	0.045
	(0.098)	(0.074)	(0.099)
Gender	-0.113	0.035	-0.069
	(0.110)	(0.084)	(0.119)
Literacy	0.230***	0.068	0.044
	(0.055)	(0.046)	(0.064)
Off farm activity	0.037	-0.026	-0.083
	(0.055)	(0.043)	(0.064)
Age	0.024**	0.009	-0.080***
	(0.012)	(0.012)	(0.017)
Squared age	-0.0002*	-0.0001	0.001***
	(0.0001)	(0.0001)	(0.001)
Remittance	-0.022	-0.475***	0.188**
	(0.076)	(0.123)	(0.091)
Fertility index	2.568**	0.662*	2.245***
	(1.056)	(0.347)	(0.310)
Slope index	-0.169	-0.050	-0.546***
	(0.202)	(0.158)	(0.195)
Altitude	-0.558	-0.082	0.077
	(0.429)	(0.361)	(0.422)
Shock index	0.134	0.147	0.725***
	(0.210)	(0.206)	(0.227)
Value of productive farm asset	-0.077	-0.159	-0.046
	(0.098)	(0.088)	(0.106)
Tropical livestock unit	-0.012	0.006	-0.022**
	(0.009)	(0.008)	(0.010)
Farm size	-0.010	0.037**	-0.036
	(0.031)	(0.018)	(0.028)
Land certification	-0.109	0.003	0.222**
	(0.076)	(0.045)	(0.089)
Credit access	0.312*	0.155	1.315***
	(0.161)	(0.098)	(0.114)

Cooperative membership	1.190***	0.030	1.378***
	(0.233)	(0.110)	(0.078)
Organic fertilizer	-11.213***	0.693	
	(3.523)	(3.543)	
Squared Organic fertilizer	0.001***	0.0001	
	(0.0001)	(0.0004)	-0.013
Cereal dummy	-0.314***	-0.498***	(0.113)
	(0.116)	(0.109)	-0.015
Pulse dummy	-0.203	-0.589***	(0.128)
	(0.127)	(0.124)	
Mean organic fertilizer	0.0001	0.0001	0.072
	(0.0001)	(0.0001)	(0.224)
Mean fertility index	-0.303	-0.447*	-0.039
	(0.222)	(0.271)	(0.314)
Mean slope index	0.179	-0.011	-0.159
	(0.286)	(0.229)	(0.282)
Mean shock index	0.101	-0.166	-0.001
	(0.258)	(0.214)	(0.000)
Mean altitude	0.001**	0.000	0.155
	(0.001)	(0.000)	(0.305)
East Tigray dummy	0.750**	0.181	-0.068
	(0.342)	(0.218)	(0.378)
South Tigray dummy	-0.276	-0.079	1.160***
	(0.403)	(0.252)	(0.438)
Metekel dummy	-0.757*	-0.059	0.639**
	(0.421)	(0.342)	(0.306)
North Gonder dummy	-0.759**	-0.433**	0.230
	(0.306)	(0.209)	(0.186)
South Gonder dummy	0.020	0.025	0.999***
	(0.238)	(0.136)	(0.210)
East Gojjam dummy	-0.250	0.309*	1.421***
	(0.251)	(0.158)	(0.231)
West Gojjam dummy	-0.380	0.056	1.551***
	(0.269)	(0.168)	(0.309)
West Wellega dummy	-0.353	-0.134	2.055***
	(0.326)	(0.228)	(0.362)
East Wellega dummy	-0.687*	-0.237	1.364***
	(0.369)	(0.278)	(0.223)
North Shoa dummy	-0.029	0.222	1.387**
	(0.234)	(0.178)	(0.540)
Assosa dummy	0.055	0.642	-0.729
	(0.499)	(0.428)	(0.577)
Kamshi dummy	0.418	0.273	-0.030
	(0.576)	(0.375)	(0.228)
Keffa dummy			
Climate information	0.388	-0.271*	1.106***
	(0.311)	(0.155)	(0.097)
Media information			0.092
			(0.123)
Extension information			0.753***

			(0.098)
Neighbor information			0.607***
			(0.130)
Market access			
			-0.003***
Household size			(0.001)
Constant			0.138***
			(0.016)
/lns1	3.637***	-6.635***	-5.947***
	(1.330)	(0.919)	(1.093)
/lns2			-0.054
			(0.050)
/r1			0.007
			(0.067)
/r2			-0.181
			(0.045)
sigma_1			0.168
			(0.212)
sigma_2			0.947
			(0.047)
rho_1			1.007
			(0.067)
rho_2			-0.179**
			(0.044)
			0.166
			(0.206)

Note: Estimation by full information maximum likelihood at the plot-level with zonal dummy, robust standard errors in parenthesis. Sample size: 4198 plots. ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level;

A3: REGRESSION RESULTS ON POOLED DATA

Dependent variable	Risk exposure for pooled data
Explanatory variables	
AWM	.717*** (0.069)
Mean temperature	0.564*** (0.038)
Squared mean temperature	-0.016*** (0.002)
Mean rainfall	0.370*** (0.040)
Squared mean rainfall	-0.001 (0.001)
Marital status	0.009 (0.063)
Gender	-0.008 (0.071)
Literacy	0.072** (0.036)
Off farm activity	-0.042 (0.036)
Age	0.012 (0.009)
Squared age	0.000 (0.000)
Remittance	-0.219*** (0.072)
Fertility index	1.303*** (0.236)
Slope index	-0.117 (0.129)
Altitude	-0.162 (0.323)
Shock index	0.223 (0.140)
Value of productive farm asset	-0.137* (0.070)
Tropical livestock unit	-0.008 (0.006)
Farm size	0.023 (0.017)

Land certification	-0.009
	(0.041)
Credit access	0.091
	(0.061)
Cooperative membership	0.324***
	(0.053)
Organic fertilizer	-2.373
	(2.695)
Squared Organic fertilizer	0.0005
	(0.0003)
Cereal dummy	-0.481***
	(0.086)
Pulse dummy	-0.518***
	(0.098)
Mean organic fertilizer	0.000
	(0.000)
Mean fertility index	-0.558***
	(0.185)
Mean slope index	0.156
	(0.188)
Mean shock index	-0.045
	(0.177)
Mean altitude	0.001
	(0.000)
East Tigray dummy	0.482***
	(0.185)
South Tigray dummy	-0.029
	(0.221)
Metekel dummy	-0.189
	(0.280)
North Gonder dummy	-0.422**
	(0.184)
South Gonder dummy	0.041
	(0.125)
East Gojjam dummy	0.168
	(0.145)
West Gojjam dummy	-0.035
	(0.146)
West Wellega dummy	-0.353*
	(0.184)
East Wellega dummy	-0.474**
	(0.219)
North Shoa dummy	0.113
	(0.133)
Assosa dummy	0.558*
	(0.329)

Kamshi dummy	0.550*
	(0.312)
Keffa dummy	-0.089
	(0.147)
Constant	-4.874***
	(0.678))

Note: Estimation by OLS (R2 =0.663) at the plot-level with zonal dummy, robust standard errors in parenthesis. Sample size: 4198 plots. ***Significant at 1% level; **Significant at 5% level; *Significant at 10% level;

A4: SELECTION INSTRUMENT TEST

Instrumental variables	Model 1		Model 2	
	Adoption of AWM 1/0		Risk exposure for non-adopters	
	Coefficient	Robust Std.Err.	Coefficient	Robust Std.Err.
Climate information	1.122***	0.094	-0.127	0.084
Media information	0.093	0.106	-0.224*	0.109
Extension information	0.646***	0.093	-0.044	0.089
Neighbor information	0.541***	0.128	-0.078	0.109
Time to the nearest market	-0.003***	0.001	0.0002	0.0007
Household size	0.133***	0.015	-0.021*	0.012
Test on instruments	chi2(6) = 274.18***		F(6, 2531) = 1.86*	
Sample size	4198		2581	

Note: Model 1: Probit model; Model 2: ordinary least squares. Estimation at the plot level with zonal dummy. * Significant at the 10% level; ** Significant at 5%level; *** Significant at 1% level.

A5: MUNDLAK'S FIXED EFFECT TEST

Dependent variable	Pooled skewness		Adoption of AWM		Risk exposure for adopters		Risk exposure for non-adopters	
	Coefficient	Robust Std.Err.	Coefficient	Robust Std.Err.	Coefficient	Robust Std.Err.	Coefficient	Robust Std.Err.
Mean organic fertilizer	-0.00001	0.00002			-0.00002	0.00004	-0.00001	0.00002
Mean of altitude	0.0006	0.0004	-0.0008*	0.0005	0.001*	0.001	0.0004	0.0004
Mean of shock index	-0.045	0.177	-0.196	0.280	0.104	0.259	-0.159	0.216
Mean of fertility index	-0.558***	0.185	0.078	0.218	-0.279	0.222	-0.447	0.275
Mean of slope index	0.156	0.188	0.045	0.310	0.178	0.288	-0.022	0.229
F-test on fixed effects	2.63**		3.91(chi-square)		1.43		1.13	
Sample size	4198		4198		1617		2581	

Note: Model: ordinary least squares except adoption column which is estimated by Probit model.

Estimation at the plot level with zonal dummy. * Significant at the 10% level; ** Significant at 5%level; *** Significant at 1% level

A6: CONDITIONAL EXPECTATIONS AND TREATMENT EFFECTS

Conditional expectations and differences	Mean values	Std. Err.
	Unpaired t-test	
$E(y_{1i}/P_i = 1)$	2.118	(0.043)
$E(y_{2i}/P_i = 1)$	1.448	(0.031)
$E(y_{1i}/P_i = 0)$	2.685	(0.036)
$E(y_{2i}/P_i = 0)$	1.925	(0.026)
$E(y_{1i}/P_i = 1) - E(y_{2i}/P_i = 1)$	0.670***	(0.053)
$E(y_{1i}/P_i = 0) - E(y_{2i}/P_i = 0)$	0.759***	(0.045)
$E(y_{1i}/P_i = 1) - E(y_{1i}/P_i = 0)$	-0.567***	(0.056)
$E(y_{2i}/P_i = 1) - E(y_{2i}/P_i = 0)$	-0.477***	(0.040)
$[E(y_{1i}/P_i = 1) - E(y_{2i}/P_i = 1)] - [E(y_{2i}/P_i = 1) - E(y_{2i}/P_i = 0)]$	-0.089***	(0.021)

* Significant at the 10% level; ** Significant at 5%level; *** Significant at 1% level