Essays on rural household decision-making under climate risk

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Essays on Rural Household Decision-Making under Climate Risk

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DISSERTATION

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by

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Kaleab Kebede Haile

DEDICATION

To my life-coach, my late mother, Shigultish Emiru.

SUMMARY

In the poverty reduction discourse, a growing attention has been devoted to correctly include considerations related to rural households' capacity to adequately manage climate risks. The introductory chapter highlights that some of the households' decisions and behavioural responses to uninsured climate risks further deepen poverty. It also reflects on the greatest development challenge that most countries in sub-Saharan Africa are currently facing related to lack of resilience of rural households to climate change and variability. In this respect, the overarching aim of this dissertation is to provide empirical evidence that can inform the design of programme and policy interventions intending to enhance rural households' capacity to take coping and adaptive responses to climate risks without sacrificing their investments on human, physical and natural capital. To this end, the three empirical chapters examine rural households' behavioural responses and decisions to better understand the impact pathways in the climate risk–welfare nexus and identify policy-related drivers for the adoption of climate-smart agricultural innovations and high-risk high-return agricultural technologies.

In Chapter 2, we link child-level longitudinal data from the Ethiopia Rural Socioeconomic Survey (ERSS) to high-resolution gridded climate data to examine the impact of climate shocks on human capital of school-age children. The results from panel regression models reveal that drought shocks have a detrimental impact on child health and schooling outcomes. Child illness is a significant mediating factor through which drought negatively affects the highest completed years of formal education. The direct and indirect (mediated) effects of drought on child schooling are disproportionately concentrated among girls. Further analyses to unpack the mechanisms show that rural households respond to drought shocks by decreasing resources allocated towards the health care of female children and relying on female child labour for non-agricultural activities. This dissertation adds to the evidence base on the climate risks-welfare nexus by investigating the gendered impact of drought-induced income shocks on human capital formation using child-level analysis. It also contributes to the literature on gender inequality in human development by examining how

gender bias in the intrahousehold resource allocation and use introduces heterogeneity in the direct and indirect effects of climate shocks on child human capital.

Chapter 3 elicits rural households' preferences for the uptake of agricultural innovations that potentially serve both climate risk adaptation and mitigation functions. A discrete choice experiment was conducted with rural households in Ethiopia to elicit their willingness to participate in a market-based environmental management scheme broadly known as payments for ecosystem services (PES) that incentivises climate-smart agroforestry. The study addresses individual- and class-specific preference heterogeneities using generalized multinomial logit and latent class conditional logit models, respectively. The results show that households derive higher utility from up-front PES payments for planting fertilizer trees. Households also strongly prefer food as the mode of payment than cash. Moreover, low numbers of mandatory planted trees and short-term contracts are found to be essential attributes of the PES scheme that can positively influence the uptake of PES contracts for growing trees on agricultural land. The results shed light on the design considerations that must be taken into account for integrating efficiency and equity objectives in PES schemes so that vulnerable rural households can be accommodated and encouraged to practice environmentally conscious land use. The study is a novel contribution to the PES literature as the design features of the scheme allow payments starting from the initial year, as opposed to conventional PES programs that pay after the ecosystem services are realized.

Chapter 4 examines the impact of rural households' uptake of weather index-based crop insurance (WICI) on their risk-aversion. This Chapter contributes to the existing literature on the causes of change in risk preferences by providing valuable insight into the structural relationship between a programme intervention that facilitates access to WICI market and farmers' risk-aversion. We collected survey and experimental data from rural households that have access to WICI in Ethiopia. The study employed the endogenous switching probit (ESP) model to address self-selection and simultaneity biases. Results from the ESP model show that farmers who purchased WICI are less likely to be risk-averse compared with non-purchasers. Similarly, non-purchasers would have attained a significant reduction in their risk-aversion if they had taken up the insurance product. We also find evidence that WICI uptake positively influences farmers' real-life risk-taking behaviour as exemplified by their decision to use mineral fertilizer. Therefore, the role of climate risk management policies and strategies in general and WICI in particular in the poverty alleviation and economic development can also be channelled through their effects on risk preferences.

Chapter 5 concludes by drawing final remarks and forwarding policy recommendations. It also highlights the study limitations and suggests potential avenues for further research.

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CHAPTER 1

INTRODUCTION

1.1 Background and Motivation

Climate change is a reality in sub-Saharan Africa (SSA) where its dire consequences are profoundly felt (Niang et al., 2014; IPCC, 2019). The countries of the Sahel, the Greater Horn, and Southern Africa are the most vulnerable to the recurrent and sometimes prolonged risk of climate shocks (Shiferaw et al., 2014). Based on the severity and geospatial coverage, disasters in SSA in relation to climate change are becoming more frequent (Masih et al., 2014). Climate change-induced shocks such as droughts, dry spells, and heat waves are increasing and will likely compromise national and regional poverty reduction goals in SSA (Rozenberg and Hallegatte, 2015; Hallegatte et al., 2016). Climate change projection models for the region also show a warming trend, frequent occurrence of extreme heat events, and erratic rainfall (Serdeczny et al., 2017).

Climate shocks severely limit progress on development and poverty alleviation in SSA mainly by incapacitating rural households[1], who play a dominant role in the economies of most countries in the region (Hertel and Rosch, 2010). The sensitivity of rural households to the vagaries of weather and climate is due to their reliance on rainfed agriculture as a source of food production and income. Consequently, poverty is disproportionately concentrated in the rural areas among agricultural households (WorldBank, 2007; FAO, 2015) that are estimated to represent three-quarters of the poor and hungry in SSA (Valdés et al., 2011).

The poverty traps literature highlights the presence of self-reinforcing mechanisms that collapse poor households into persistent poverty as a result of their exposure to serious and frequent climate shocks (Carter and Barrett, 2006; Dercon and Christiaensen, 2011; Tittonell and Giller,

[1]Rural households (agricultural households), who are predominantly family farms operating on less than 2 hectares of land, represent around 80 percent of the total farmlands and up to 70 percent of the national population in SSA (Lowder et al., 2016).

2013; Barrett et al., 2016). The inability of the households to withstand climate shocks in one season can have significant long-lasting impacts on their well-being during the post-shock periods (Hertel and Rosch, 2010). Evidence show that drought-induced malnutrition and children's dropout from school can irreversibly impair human capital development with long-run costs on future earnings (Dercon and Hoddinott, 2004; Maccini and Yang, 2009; Woldehanna and Hagos, 2015; Adhvaryu et al., 2018). Moreover, the combined effect of reduced consumption and loss of property attributed to drought cause a significant decline in the household income over a decade ex-post (Clarke and Hill, 2013).

Under these circumstances, the greatest development challenge currently facing most countries in SSA is enhancing climate resilience of rural households. Goal 13 of the UN's sustainable development goals (SDGs) recognizes that tackling climate change and mitigating its welfare impact requires enhancing climate resilience of households in developing countries. The climate resilience framework is a nascent approach for describing and understanding households' capacity to anticipate, adapt to, and recover from the effects of a shock in a manner that protects livelihoods, and supports economic development (Constas et al., 2014). The framework aims to capture all possible interrelated household decision-making to maintain or improve specific well-being outcomes (food and nutrition security, health, education) in the presence of climate shocks. Attaining climate resilience requires households to utilize the most effective combination of short- and long-term strategies (Frankenberger et al., 2012; Béné et al., 2015) that would enable them to break the cycles of poverty (Barrett and Constas, 2014; Constas et al., 2014; Cissé and Barrett, 2018). Hence, building households' resilience would require promoting desirable coping responses and production choices that would strengthen preparedness and adaptation to climate risks. The conceptualization of climate resilience reflects the idea that it is about agency and capacity of households to make decisions that have positive consequences on their own lives Béné et al. (2014).[2] What remains for researchers and development practitioners is to adequately incorporate the concept of climate resilience in the design and evaluation of policy and programme interventions that intend to alleviate poverty and spur economic development in SSA.

This dissertation provides a theory-based investigation into the effects of climate shocks and climate risk management policies and strategies on rural household behavioural responses and decision-making to better understand the impact pathways in the climate risk–welfare nexus and identify market-based drivers for the adoption of climate-smart agricultural innovations and high-risk high-return agricultural technologies. This facilitates designing evidence-informed policy and programme interventions that intend to maintain or improve household investments on human, physical and natural capital in the face of climate change.

There are few rigorous studies that examined the effectiveness of households' decisions and responses in managing climate shocks. A study by Niggol Seo (2012) shows that rural households in SSA manage income and consumption shocks arising from climate risks by shifting across farm-

[2] It should be noted that not all of the households' ex-ante and ex-post responses and decisions to uninsured climate shocks will eventually lead to positive well-being results in the long-run (see section 1.4).

ing systems. A more recent study by Gao and Mills (2018) analysed the impact of weather shocks and the mitigating role of alternative coping strategies on household consumption and income. These studies only focus on household level analyses and hence implicitly assume that the welfare effects of climate risks are equally redistributed among different demographic groups in the household. Studies by Hoddinott (2006), Zamand and Hyder (2016), Nguyen and Minh Pham (2018) show that children are the most vulnerable household members and may suffer disproportionately from the consequences of climate shocks. However, there remains a research gap that has limited rendering empirical explanations on plausible mechanisms related to household decision-making which may result in unequal allocation of resources to health care and schooling within rural households in the context of SSA. In this regard, the only exceptions are studies by Jensen (2000), Björkman-Nyqvist (2013), Rabassa et al. (2014) and Valero (2018). The findings of these studies are inconclusive concerning the presence of gender bias in the intrahousehold resource allocation when household income is constrained by climate shocks. This dissertation adds to the evidence base on the climate risks-welfare nexus by investigating the gendered impact of drought-induced income shocks on human capital formation using child-level analysis. In doing so, it investigates whether and how intrahousehold resource allocation and use introduce heterogeneity in the direct and indirect effects of climate shocks on child human capital based on gender.

Climate shocks affect human capital of children with long-lasting negative consequences on their income generating prospects (Dercon and Hoddinott, 2004; Maccini and Yang, 2009; Abiona, 2017; Adhvaryu et al., 2018), and thus dictate intergenerational poverty transmission. When extreme weather events become too severe and too frequent, from the lens of climate change adaptation and mitigation, building households' adaptive capacity reduces the extent, depth and transmission of poverty (Di Falco and Veronesi, 2013; Carter and Janzen, 2015). Climate-smart agricultural innovations may enhance rural households' capacity to adapt to and mitigate the effects climate shocks and ensure stable household income. Easing households' liquidity constraints may eliminate adverse coping responses that lead to diverting spending away from child health care and schooling. Despite this potential, the uptake of climate-smart agricultural innovations by rural households in sub-Saharan Africa (SSA) remains low (Garrity et al., 2010; Glover et al., 2012). Promoting large-scale adoption of climate-smart agricultural innovations across the landscapes of SSA has been an agri-environmental policy challenge. One possibility is to introduce incentives under the market-based environmental management scheme broadly known as payments for ecosystem services (PES) to induce large-scale adoption of environmentally responsible practices, which also enhance rural households' capacity to manage climate risks.

PES schemes mainly focus on conservation- and restoration-oriented ecosystem service provision via land retirement (Hjerpe et al., 2015). Moreover, the existing PES arrangements are more suitable for well-off farmers with well-defined property rights, low transaction costs, and better resource endowment (Sierra and Russman, 2006; Bremer et al., 2014; Lansing, 2017). In the context of SSA, land rights are poorly enforced Wily (2011), and retiring private agricultural lands for environmental conservation contradicts with the region's policy agenda that aim to increase agricultural production to feed the growing population. Studies by Jack (2010), Porras (2010), and Cranford and Mourato (2014) attempt to address this challenge by considering the eligibility of climate-smart agroforestry on private agricultural lands under PES financing mechanisms. However, as any conventional PES program, the payment arrangements in their studies are ultimately attached to the actual provision of environmental services. As a departure, this dissertation proposes a novel design feature of a PES scheme which provides up-front payments to enable rural households invest in climate-smart agroforestry. Therefore, the proposed PES scheme attempts to serve as part of the overall climate risk management strategy by ensuring the inclusion of poor and vulnerable rural households, and correcting market failures that lead to the undersupply of climate risk mitigating services in SSA.

The uptake of market-based climate risk management strategies may influence individual risk preferences and consequently affects how people behave and make production, consumption and labour supply decisions. Individual risk attitude is a significant determinant of households' decisions on farm enterprise combinations (Nyikal and Kosura, 2005), higher education attainment (Brown et al., 2012), and adoption of agricultural technologies (Liu, 2013; Ward and Singh, 2015; Brick and Visser, 2015; Holden and Quiggin, 2017). The canonical approach in modelling household decision-making assumes that risk preferences are fixed behavioural parameters that are not affected by changes in the market environment in which individuals make their decisions. However, risk preferences and the availability of markets and institutions that facilitate risk bearing are not independent (Palacios-Huerta and Santos, 2004; Mendola, 2007). In this regard, in the absence of crop insurance markets, rural households will rely on "self-insurance" (Rosenzweig and Binswanger, 1993), which may lead to formation of risk-averse attitudes. This dissertation provides a novel empirical evidence on the effect of weather index-based crop insurance (WICI) market on farmers' risk preferences and explores one of the possible causes of change in individual risk attitude, a major driver of agricultural technology adoption.

1.2 Objective and Research Questions

The main aim of this dissertation is to provide a broader understanding of the changes in rural household economic behaviour and decision-making, which determine their immediate and future income generating capacities, in response to climate shocks and climate risk management policies and strategies. It presents valuable insights for designing resilience-promotive policies that would help households in Ethiopia and possibly across SSA to break out of poverty traps and enjoy virtuous cycle of increasing income. To this end, the dissertation addresses the following specific research questions:

- What are the gender differentiated impacts of drought shock on human capital – child health and education? (Chapter 2)

- What design features of a payments for environmental services scheme influence rural households' willingness to adopt climate smart agroforestry which serves climate change adaptation and mitigation functions? (Chapter 3)
- What are the impacts of formal climate risk transfer mechanisms such as weather-index based crop insurance schemes on risk attitude and behaviour of rural households? (Chapter 4)

1.3 Research Setting and Data

In this dissertation, the focus is one sub-Saharan African country, Ethiopia. In Ethiopia, like most countries in SSA, agricultural households represent the majority of the population and frequent climate shocks are becoming the new normal in the region. More than 80 percent of the total population[3] in Ethiopia resides in rural areas (CSA, 2013) where their livelihoods directly or indirectly depend on rain-fed agriculture. As a result, these households are more vulnerable to poverty and hunger due to their sensitivity to the vagaries of weather and climate. Climate shocks constrain the households' capacity to maintain smooth consumption of basic goods and services by compromising income. Climate model predictions show a very likely increase in temperature in Ethiopia by 2.2°C in the mid-21st century (Conway and Schipper, 2011). Consequently, the country is going to face more climate-related aggregate shocks. Rural households will be disproportionately affected by increasing stresses to water availability, agricultural production and income, and wages and prices (Kahsay and Hansen, 2016). At the macro level, aggregate shocks caused by climate change can reduce Ethiopia's GDP by 8 to 10 percent in 2050, compared to the counterfactual scenario of no climate change baseline (Robinson et al., 2013). Therefore, building climate resilience of households is a vital approach to alleviate shock-induced income loss at micro and macro levels.

1.4 Conceptual Framework

The search for an explanation of rural households' decision-making in both perfect and incomplete market contexts led to the formulation of the agricultural household model (AHM). In the model, an agricultural household is both a producer who chooses the allocation of labour and other inputs to farm production, and a consumer who chooses the allocation of income from profit and labour sales to the consumption of goods and services (Singh et al., 1986; Taylor and Adelman, 2003). The household maximizes utility through the consumption of all available commodities (i.e., home-produced goods, market-purchased goods, and leisure), subject to households' budget constraints (Mendola, 2007). In AHM, the household division of labour is explained according to principles of comparative advantage; individual labour is allocated to tasks with lower opportunity cost (Evans, 1991).

At the core of AHM is the issue of whether the household's production, consumption, and labour supply decisions are simultaneously determined or if they are separable. If rural households

[3] The total population of Ethiopia is estimated to be 110 million in 2017 (CSA, 2013).

have access to competitive markets for factors of production, outputs and future contingencies (i.e., credit and insurance), prices are exogenous and production risks can be completely diversified resulting a separable decision-making process (Roe and Graham-Tomasi, 1985). As such, production decisions (input use, adoption of farm technology and output choice) affect consumption exclusively via income levels, and production decisions are entirely independent of consumption. However, in most developing countries, markets related to land resources, inputs, credit, insurance, and some basic commodities are incomplete, function poorly or may have high transaction costs for rural households (de Janvry et al., 1991). Hence, the decision process becomes non-separable (circular) (Singh et al., 1986; Taylor and Adelman, 2003; Mendola, 2007); an agricultural household as a consumer and supplier of labour affects its behaviour as a producer, and vice versa. Hence, any reductions to their agricultural production can have a significant impact on food and income available for consumption purposes (Hertel and Rosch, 2010), and consequently the households respond by altering their production and labour supply decisions. In these circumstances, it is vital to consider the effects of climate shocks and liquidity constraints generated by market imperfections to examine rural households' decisions and behavioural responses that ultimately determine their vulnerability to persistent poverty.

For rural households, to be poor goes beyond substantial deprivations in food, shelter and clothing in one particular period, it is also about being exposed to severe and frequent climate shocks and their defenselessness against these shocks (Rozenberg and Hallegatte, 2015), which have repercussions not only on their immediate welfare indicators during the shock period but also on their post-shock income earning capacities (Hallegatte et al., 2016, 2017). In this dissertation, defenselessness of rural households is conceptualized as their lack of options and resources necessary to choose from a range of effective response strategies to manage climate risks in a way that will retain or improve their current and future well-being. The absence or inaccessibility of formal credit and insurance markets limits rural households' options to adequately absorb climate shocks that they constantly face (Harvey et al., 2014; Karlan et al., 2014). In this regard, the welfarist assumption of the existence of competitive markets will not hold in the context of rural households in SSA. Therefore, the long-term welfare outcomes of rural households are determined not merely by the immediate impact of the climate shocks – such as loss of crop and livestock – but also by the effect of climate shocks on their behavioural responses that govern their non-separable consumption, production and labour supply decisions.

In the poverty reduction discourse, a growing attention has been devoted to correctly include considerations related to managing climate risks. Some of the households' decisions and behavioural responses to climate shocks further deepen poverty. As an adaptive response, farmers usually modify their production practices to safer but low-return activities as a means of providing "self- insurance" (Rosenzweig and Binswanger, 1993; Holzmann and Jorgensen, 2001). Similarly, rural households avoid the uptake of climate change adaptation and mitigation strategies, which do not provide immediate cash returns, due to the disutility associated with the direct and opportunity costs of investing in the strategies (Neufeldt et al., 2011). Though such adaptive responses may help reduce income fluctuations in the short-run, they are usually costly in terms of forgone opportunities for farm income gains that could be attained through agricultural investments and adoption of agricultural technologies (Barrett et al., 2006; Dercon, 2006; Hill et al., 2019). Ex-post, the exposure of farm households to uninsured climate shocks triggers adverse coping decisions that could result in a deprivation in their current and future welfare indicators.

In the prevalence of drought risk, the possible coping responses with long-lasting negative consequences on human capital may include reducing both the number of meals eaten per day and the quantity of food consumed per meal, withdrawing children from school, and diverting spending away from healthcare (Pandey et al., 2007; Hill, 2009; Woldehanna and Hagos, 2015; Janzen and Carter, 2018). In particular, children have the highest probability of falling into a disadvantaged position for their entire lifetime (Maccini and Yang, 2009; Clarke and Hill, 2013). Such inefficient ex post climate risk management measures could have long-term negative consequences in terms of depriving human capital of children, and aggravate inter-generational poverty transmission. Gender bias in the intrahousehold resource allocation and use based on parents' perceived values of child labour is a crucial socio-cultural element that may dictate whether boys or girls bear the burden of the income effect of climate shocks (Björkman-Nyqvist, 2013; Valero, 2018). Thus, gender bias may introduce variations in the within-household food allocation, health care and schooling expenditure, and child labour use that have direct and indirect effects on human capital formation of children. Failure to consider the gender-disaggregated effects of climate shocks and households' coping responses limits the insight required to design climate risk management strategies and policies that intend to buffer household income and spur human development in the face of climate change.

The income effect of climate shocks on rural households' welfare is further aggravated by their lack of willingness to invest in natural capital, which renders climate risk management benefits. In the spirit of the reference-dependent utility model of Köszegi and Rabin (2006), the overemphasis households give to the loss in utility as a result of a decline in their reference (i.e. status quo) consumption level could explain rural households' lack of uptake of climate-smart practices − major sources of natural capital on agricultural land. In the short run, adopting agricultural practices with climate change adaptation and mitigation benefits involves incurring direct and opportunity costs without immediate economic returns. Poor households that are at the bare minimum in their current consumption cannot afford any decline in their current subsistence income, and hence find it hard to invest on the practices that generate natural capital. As a result, short-term income losses often inhibit rural households from investing in climate-smart practices which provide long-term economic and environmental returns (Neufeldt et al., 2011; Ndah et al., 2014). The standard policy intervention in the face of positive environmental spillovers is to introduce incentives so that private individuals benefit from the use of environmentally responsible practices (Martin et al., 2014; Reed et al., 2015). Recently, PES draws a lot of attention among researchers and policymakers alike as a market-based approach to internalizing the positive externalities of land use decisions. If a PES program compensates rural households for the direct and opportunity costs of investing in climate-smart agroforestry on their agricultural land, the disutility to the households may be avoided and leave them indifferent between the status quo and adoption of the practice which has climate change adaptation and mitigation functions. Therefore, PES may serve as part of the overall climate change adaptation and mitigation strategy by inducing a change in behaviour among rural households in favour of adopting climate-smart agroforestry.

Moreover, the accessibility of formal credit and insurance markets to rural households enhance their ability to withstand the effects of climate shocks (Karlan et al., 2014), and has been a key determinant of agricultural investments, which yield physical capital. As a crucial determinant of economic outcomes, markets dictate the formation of values, tastes and preferences of individuals by influencing them to perceive a different world and affecting what they must do or be to sustain their livelihood (Gerber and Jackson, 1993; Bowles, 1998; Palacios-Huerta and Santos, 2004; Melesse and Cecchi, 2017). Specifically, WICI schemes that provide a transparent risk transferring mechanism for rural households may help them better manage climate risks and exhibit risk-taking behaviour in their production decisions (Barnett et al., 2008). WICI markets may eliminate what Rosenzweig and Binswanger (1993) call farmers' need for "self-insurance" by changing farmers' interpretation of the operating environment for farming, and ultimately may reduce their risk-aversion. Consequently, WICI may affect their economic risk-taking behaviour in daily life as the reduction in risk-aversion determines household decisions to invest in high-risk but profitable agricultural technologies (Liu, 2013; Ward and Singh, 2015; Brick and Visser, 2015; Holden and Quiggin, 2017).

In light of the above discussions, Figure 1.1 presents the conceptual framework of the dissertation by laying out the pathways (channels) through which climate shocks and climate risk management policies and strategies affect households' decisions to invest in child human capital, climate-smart agricultural innovations and high-risk high-return agricultural technologies. Climate shocks may cause low and variable income and consumption that may influence their economic behaviour and decision-making. Households may respond to climate risk-induced income shocks by altering intrahousehold resource allocation and use of child labour as ex-post (coping) responses which determine the extent of deprivations in child human capital − child health and education. In this respect, gender bias is a vital mechanism that may introduce heterogeneity on the impacts of climate risk-induced income shock on human capital based on sex of the child (Chapter 2). Ex-ante, market-like environmental incentives such as PES enable rural households to bear short-run costs associated with investments in climate-smart agroforestry, which yields delayed (long-term) income gains and mitigates climate change (Chapter 3). Formal climate risk transfer mechanisms such as WICI could relax household liquidity constraint during shock periods and bring about desirable economic behaviour to leverage higher-return investments in agricultural technologies that ultimately determine households' immediate income generating capacity (Chapter 4). Enhancing rural households' immediate and long-term income generating capacity may reduce their vulnerabilities to climate shock-induced deprivations in human, physical and natural capital.

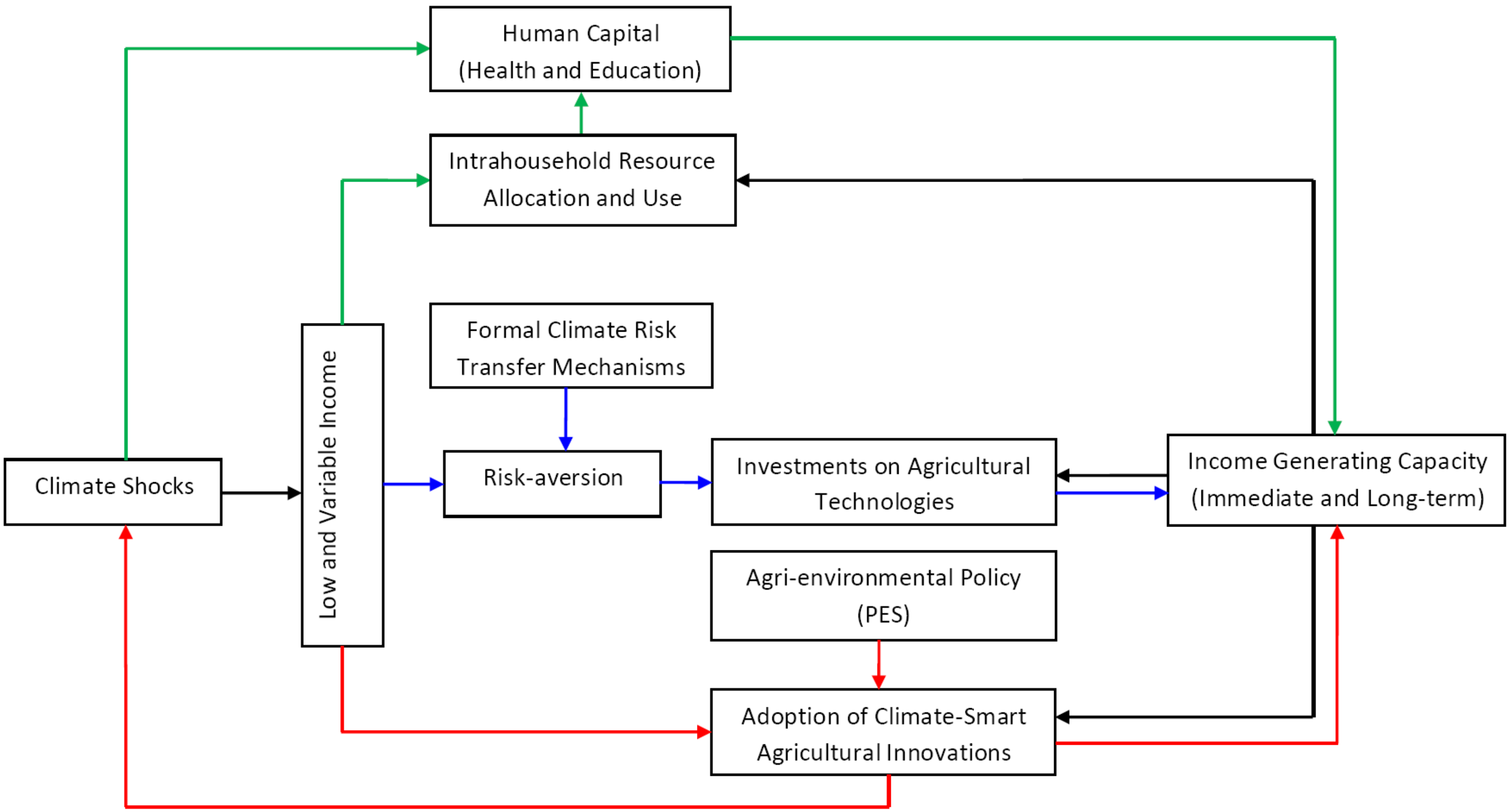

Figure 1.1: Conceptual Framework of the Dissertation: Chapter 2 in Green, Chapter 3 in Red, and Chapter 4 in Blue

1.5 Organization of the Study

This dissertation is organized in five chapters. The first chapter is the general introduction comprising the background and motivation, research questions, geographical focus area, and conceptual framework of the dissertation. In the presence of uninsured climate risks, Chapter 1 highlights the presence of self-reinforcing mechanisms related to household behavioural responses and decision-making that trap rural households in persistent poverty.

Chapter 2 presents empirical work that examines the gender differentiated impacts of drought shocks on reported child illness and schooling outcomes, as measured using school attendance and the highest grade completed of school-aged children. In so doing, it adds to the body of knowledge on the climate shocks-human capital nexus by presenting gender-disaggregated assessments to test whether the impacts of drought on child human capital vary conditional on sex of the child. To this end, child-level data from the Ethiopia Rural Socioeconomic Survey (ERSS) panel data were merged with high-resolution geo-referenced climate data. The results from within-child variation estimators reveal that drought has a detrimental impact on the health status and highest grade completed of children. The impact of drought on child human capital is disproportionately large among female children. The chapter also presents separate analyses that investigate the impact pathways. Accordingly, the impact of drought on child health appears to be more notable among female children as they are disfavoured by the intra-household resource allocation to health care in the presence of drought-induced income shocks. Consequently, the negative effect of drought on a female child's completed years of formal schooling is channelled, albeit not entirely, through ill health. This result is robust to using recursive bivariate estimation with exclusion restriction to correct for biases associated with the endogeneity of child health. Moreover, households also increase the use of female child labour for non-agricultural activities, which is consistent with drought bearing a robust direct negative impact on schooling of female children besides its mediated effect through ill health. These findings imply that the design of policy and programme interventions aiming to buffer household income from the effects of climate shocks should also, as a conditionality, take into account to eliminate adverse coping responses that lead to gender inequalities in human development.

Chapter 3 examines rural households' preferences for uptake of agricultural innovations with economic and ecosystem benefits in response to being incentivised under a PES scheme. The study is a novel contribution to the PES literature as the design of the scheme features payments starting from the initial year, as opposed to conventional PES programs that pay after the ecosystem services are realized. As such, the Chapter attempts at integrating efficiency and equity concerns in a PES scheme so that it is attractive for poor and vulnerable rural households to adopt climate-smart agroforestry, which has has delayed economic and climate risk mitigating benefits. A discrete choice experiment was conducted to elicit the households' preferences to participate in the PES scheme in Ethiopia. Attributes evaluated are "number of planted trees", "payment amount", "payment type", and "contract period" of the PES scheme. The econometric analyses using the generalized multinomial logit and latent class conditional logit models account for the presence of farmer- and class-specific preference heterogeneities in the choice behaviour of households. The results show that households derive higher utility from up-front payments. They are willing to receive lower annual payments if the payments are in food rather than cash. Households also strongly prefer low numbers of mandatory planted trees and short-term PES contracts. These findings shed light on the considerations that must be accounted for when designing and implementing environmental policies such as PES schemes that promote large-scale adoption of agricultural innovations to transform rainfed agriculture in SSA into a climate resilient farming system.

In the absence of climate risk management policies and strategies, farmers in developing countries are generally assumed to be risk-averse as a self-insuring mechanism to avoid income variability. Chapter 4 examines the effect of rural households access to a formal climate risk transfer mechanism on their risk-aversion. Previous studies take risk-aversion as a primitive behavioural parameter that is not affected by changes in the market and institutional environment in which individuals render their decisions. Instead, this Chapter takes a crop insurance market as a domain that may change individual risk-aversion in the context of developing agrarian economies, and contributes to the small but growing literature on the causes of change in individual risk-aversion. Survey and experimental data were collected from smallholder farmers that have access to WICI in Ethiopia. While establishing the relationships between WICI and farmers' risk-aversion, the econometric analysis in this chapter takes into account self-selection and simultaneity biases. Furthermore, the chapter explores the variation in farmers' decision to adopt risky but profitable agricultural technologies − as exemplified by mineral fertilizer use − attributable to WICI uptake. In doing so, it demonstrates that a change in risk-aversion is a plausible channel that affects real-life risk-taking behaviour of farmers. The findings of Chapter 4 imply that formal climate risk transfer mechanisms can contribute to poverty alleviation and economic development within agrarian economies by bringing up desirable individual economic behaviour.

Chapter 5 concludes by drawing final remarks, policy implications, limitations of the research, and avenues for further study.

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CHAPTER 2

CLIMATE SHOCKS, COPING RESPONSES AND THE GENDER GAP IN HUMAN DEVELOPMENT*

Abstract

This study examines the impact of drought on child health and schooling outcomes and investigates the impact pathways related to household decision-making. We merge child-level longitudinal data from the Ethiopia Rural Socioeconomic Survey (ERSS) with geo-referenced climate data. Our findings from within-child variation estimators reveal that drought has a detrimental impact on health status and highest grade completed of children. While drought significantly increases reported child illness among both sexes, the impact appears to be more notable for female children. Similarly, the educational impact of drought is disproportionate among female children. We show that the negative effect of drought on a female child's completed years of formal schooling is channelled, albeit not entirely, through ill health. We find that households respond to drought-induced income shocks by decreasing the allocation of resources for the medical treatment of an ill female child. Moreover, households also increase the use of female child labour for non-agricultural activities, which is consistent with a disproportionate increase in school absenteeism of older girls during drought. Thus, gender bias in the intrahousehold resource allocation and use explains why the direct and mediated schooling effects of drought are concentrated only on female children. We discuss how gender-responsive policy design may help alleviate gender inequality in human development in the face of climate change.

Keywords: Drought, coping capacity, human capital, gender bias, sub-Saharan Africa, Ethiopia

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2.1 Introduction

Households in sub-Saharan Africa (SSA) are disproportionately affected by climate change due to their often limited capacity to withstand its negative effects without sacrificing utilization of basic goods (food) and services (health and education) (Harvey et al., 2014; Seaman et al., 2014). Particularly children are among the most vulnerable household members and may suffer unduly from the consequences of climate shocks. A growing body of research has shown that climate shocks can impair human capital development of children (Hoddinott, 2006; Thai and Falaris, 2014; Zamand and Hyder, 2016; Duque et al., 2018; Nguyen and Minh Pham, 2018) with irreversible long-lasting effects on their lifetime earning capacities (Dercon and Hoddinott, 2004; Alderman et al., 2006; Maccini and Yang, 2009; Abiona, 2017; Adhvaryu et al., 2018). Hence, climate shocks not only deteriorate the immediate welfare indicators of children but may also determine their lifetime socioeconomic status. Children with low human capital levels are most likely to create new poor families because of their consequent lower living standards and reduced prospects of social mobility in adulthood (Case et al., 2011). Promoting human capital development early in life may break this vicious cycle of intergenerational poverty transmission and enable young people to choose between different livelihood strategies that may, in turn, reduce their vulnerability to climate change. Moreover, these microeconomic gains may translate into human capital accumulation and sustainable development at the macro level in the long-run (Horton and Steckel, 2013).

Climate shocks affect child health and schooling outcomes – the two main building blocks of human capital – via income (see Baez et al. (2010), Phalkey et al. (2015) and Hanna and Oliva (2016) for recent reviews). The impact of income shocks on human capital may however not be evenly distributed across all children in the household. Gender bias in the intrahousehold resource allocation may play a significant role in determining who bears the brunt of climate change between boys and girls. Moreover, gender-based variations in demand for child labour within the household can also serve as a channel through which climate shocks affect child schooling (Björkman-Nyqvist, 2013). The existing evidence on gender bias mainly comes from Asia, and shows that parents' gender preferences play a significant role in determining child health and education (Pande, 2003; Himaz, 2010; Jayachandran and Kuziemko, 2011; Azam and Kingdon, 2013; Sivadasan and Xu, 2019). By contrast, in the context of SSA where climate risk-induced income shocks widely prevail, households' differential resource allocation and use decisions, which affect children's health and education, conditional on gender are rarely studied (Rossi and Rouanet, 2015; Valero, 2018). In this vein, the existing few studies provide mixed and inconclusive results; either no evidence of gender-based discrimination (Jensen, 2000; Rabassa et al., 2014) or gender bias against girls (Björkman-Nyqvist, 2013; Valero, 2018).

However, there is concern about the extent to which we can causally interpret the results of previous studies unless the effects of climate shocks are estimated for a given child over multiple time periods. Di Falco and Vieider (2018) argue that while it has been a common practice to use an objective measure of climate shock (i.e. deviation from historical mean rainfall), which is an exogenous variable, it does not mean the shock is random enough to ensure that all areas in a given country and all individuals in a given area have an equal probability of being affected. Moreover, previous empirical studies rely on accounting for community or district fixed effects. This approach completely ignores the effects of child- and household-level unobserved heterogeneities that may determine the extent of individual-level effects of climate shocks. For instance, by using community fixed effects, heterogeneities in gender bias across households cannot be accounted for without imposing a strict assumption of the equality of gender bias at the household and community level. We, instead, rely on within-child variation estimations by taking a given child and comparing the changes in human capital with herself to identify the impact of climate shocks. Our approach considers that every child is unique, and thus, the direct and indirect effects of climate shocks on human capital may not be similar for everyone in a given household that resides in a higher-level cluster (community or district).

Furthermore, previous empirical studies examine the effect of climate shocks on either child health or schooling separately. The possible short-run link between child health and education outcomes, and how this relationship may vary between boys and girls in the face of climate shocks is not adequately investigated. To our knowledge, this study is the first empirical evidence that provides a gender-disaggregated investigation of the contemporaneous causal relationship between child health and a common set of schooling outcomes – school absenteeism and highest grade completed – in the presence of climate shocks and tests whether climate shock-induced ill-health serves as a mediating channel. We also assess the extent to which gender bias in child health care, schooling, and labour use, if exists at all, results in gender gap in education in Ethiopia.

Like most countries in SSA, Ethiopia is going to face more climate-related aggregate shocks. In 2050, temperature in Ethiopia is expected to rise by 2.2^0C which will drastically increase the frequency of severe heatwaves and droughts (Conway and Schipper, 2011). The effect of a worsening climate on rural households in Ethiopia will be mainly channelled through its impact on food production, income and prices (Brown and Funk, 2008; Saronga et al., 2016; Shumetie and Yismaw, 2018). In this regard, understanding the underlying demographic, socioeconomic and environmental conditions that determine households' decision-making process, mainly concerning the use and distribution of resources within the household, would facilitate identifying appropriate design features of a policy or programme intervention to target the most vulnerable groups. This is of great importance to increase the effectiveness of the intervention in buffering human development – food and nutrition security, health status, and education – from the effects of climate shocks and ensure inclusive growth in Ethiopia.

Our analyses are based on child-level balanced panel data from three rounds (2011/12, 2013/14, and 2015/16) of the Ethiopia Rural Socioeconomic Survey (ERSS) matched with georeferenced climate data. We use within-child variation estimators to identify the causal effect of drought on human capital. Our results show that drought significantly increases reported child illness of both sexes. However, the schooling impact of drought is robust only for female children. The negative effect of drought on the highest grade completed of female children is channelled, albeit not entirely, through illness. This finding is robust to using recursive bivariate estimations with an exclusion restriction to correct for biases associated with the endogeneity of child health due to time-varying unobserved heterogeneities. As impact pathway, we find that households respond to drought shocks by adjusting their resource allocation to health care services and use of child labour in a manner that disfavour a female child, who consequently bears the adverse direct and mediated schooling effects of drought.

In considering the impact of climate shock-induced health impediments on schooling of children, our contribution is distinct from those that explore the intertemporal shock-human capital synergies. Studies by Dercon and Hoddinott (2004), Alderman et al. (2006), Maccini and Yang (2009), Shah and Steinberg (2017), Adhvaryu et al. (2018) demonstrate that climate shocks have a detrimental effect on early life health endowments via nutrition and influence future educational outcomes of children. A principal finding that emerges from such exercise is that shock-induced child health impediments in utero and during infancy and early childhood (preschool years) have lifelong effects on health, education and socioeconomic outcomes. This provides a powerful rationale for prioritizing policy interventions that target unborn children, infants and preschoolers for improvements in human development.[1] Concerning gender bias in early life and its long temporal reach, while Maccini and Yang (2009) find that early-life rainfall has strong positive effects on human capital and socioeconomic status of women, but not of men, Dercon and Hoddinott (2004) find no evidence that girls suffer more than boys regarding the impact of early-life drought on their long-term wellbeing – health, education and lifetime earnings during adulthood. However, there is much less known on how climate shock-induced poor health affects older children, in particular those of school-going age, conditional on gender. We hypothesize that climate shocks happening to children of school-going age may generate different health effects and gender-based household coping responses from shocks happening to pre-schoolers, infants, and unborn children. Moreover, studying children of school-going age allows for a direct investigation of the potential short-run relationship between ill-health and schooling outcomes.

The analytical challenge in estimating a contemporaneous causal effect of health status on education is discussed in Behrman (1996) and Glewwe and Miguel (2007). They emphasised that the mere inclusion of health status – where child nutrition usually serves as an intermediate indicator – on the right-hand side of the child schooling model may introduce endogeneity and thus cannot guarantee a causal interpretation on the estimated coefficient. Without the context of climate shocks and gender-disaggregation, Ding et al. (2006) and Aturupane et al. (2013) address this issue and estimate the contemporaneous causal effect of child health on academic performance by making use of an instrumental variable approach. They, however, implicitly assumed that the effect of child health on education is the same for all children regardless of gender. In contrast, we examine the impact of drought on health among school-age children in Ethiopia, and subsequently how contemporaneous adverse health effects affect a child's schooling outcomes conditional on gender.

[1] Early childhood interventions are long-term economic investments that have favourable effects on economic outcomes during adulthood (Hoddinott et al., 2008) and in most contexts have the highest rates of returns (Alderman et al., 2017).

The rest of the paper is organized as follows. Section 2.2 presents the conceptual framework focusing on climate shocks-gender-human capital nexus. Section 2.3 describes the source of data and descriptive statistics. Section 2.4 explains the identification strategy. Section 2.5 presents the econometric results and discusses the main findings. Section 2.6 concludes and offers policy recommendations.

2.2 Conceptual Framework

Climate change disproportionately affects rural households in SSA as their livelihood depends on rainfed agriculture. For uninsured and liquidity constrained rural households, climate-related negative income shock has repercussions on household current-period investment in child human capital (Jensen, 2000) by raising the costs of education[2] and health care[3] relative to household income (Ferreira and Schady, 2009). The decision to curb household human capital investment in response to income shocks may differ across children based on parents' perceived values of child labour and returns to their investment. Gender is an important sociocultural element that may introduce variations in individual allocations within a household, and may dictate who bears the burden of the income effect of climate shocks among boys and girls.

Gender roles in the society have a substantial effect in shaping parents expected costs and returns of human capital investment within the household.[4] The origins of gender roles are linked to the form of agricultural activities practiced in the society. The descendants of societies that traditionally practiced plough agriculture today have persistent less equal gender norms that discriminate against women's participation in the workplace, politics, and entrepreneurial activities (Alesina et al., 2013). In these societies, the prevailing discriminatory gender norms give women subordinate status in the community. This compels parents to perceive lower private returns to girl's labour and education, and consequently prioritize investments in human capital of boys. However, and of key interest here, perceived returns, which affect child human capital investment decisions, are lower than actual returns (Jensen, 2010). In the context where the majority of rural households are illiterate and less-informed, and the prevailing gender norms discriminate against women, it is highly likely that parents substantially underestimate the returns to their investment in human capital of female children. As such, households underestimate the costs of gender bias as they assign lower values to female children's labour and economic contributions to the household.

Therefore, unequal gender role attitudes interact with the income effect of climate shocks in reinforcing gender bias in household decision to invest less in a female child's health and education. In the prevalence of gender norms that assume women's roles are limited to attending unremunerated domestic and reproductive tasks, rural households expect lower private returns[5] to female

[2] While the direct costs are related to school fees and supplies, the opportunity cost is the reduction in household income due to loss of the child's labour for agricultural, non-agricultural and wage-paying activities (Alderman et al., 2012).

[3] Health care systems in SSA heavily rely on user (out-of-pocket) fees for the health services and prescribed medicines (Meessen et al., 2011; Ali, 2014; Masiye et al., 2016).

[4] While households in most sub-Saharan African countries display gender preference for variety or no preference at all, this does not mean absence of unequal attitudes toward gender roles (Rossi and Rouanet, 2015).

[5] It is attainable to assume that rural households do not have adequate information to anticipate possible gender discriminations in high-skill

education. Moreover, the livelihood of the majority rural households in SSA depends mainly on physically intensive productive activities than on mental tasks, disfavouring girl's comparative advantage and lowering their opportunity cost of labour than that of boys. In this light, parents may enforce health and physical well-being of boys expecting higher returns from their productive tasks, particularly in agriculture. Consequently, female children that have lower investments in nutrition and use of medical services during shock periods are more likely to have poor health status. It should be noted that ill health adversely affects schooling, and hence further widens the gender gap in education.[6] In this respect, when rural households experience climate-risk induced income shocks, while male children are protected, they divert their human capital investment spendings away from female children. This has far reaching repercussions by generating feminized poverty trap. Rural households that live in a society with discriminatory gender norms against women, assuming they are only capable of handing low value tasks inside the household, see less value in investing in human capital of female children. Ultimately, female children with low human capital become women with low earnings and socioeconomic status, and thus with limited capacity to financially support parents. This completes the vicious cycle by perpetuating gender bias against household investment in human capital of girls.

In sum, in the face of climate shocks, gender biases may introduce variations in the within-household food and labour allocations, and investments in health and education, and hence result in two separate human capital investment decisions based on sex of the child. "The cultural institutions favouring males might themselves fade naturally with economic modernization, enabling gender gaps to close, but there is also scope for policy makers to expedite the process" (Jayachandran, 2015, p. 84). An empirical investigation on the effect of climate shocks on household investment in child human capital conditional on gender has valuable policy implications in prioritizing climate disaster responses that intend to mitigate gender bias against school-aged female children, and alleviate gender inequality in human capital development in SSA.

2.3 Data and Descriptive Statistics

2.3.1 Source and type of data

We use the Ethiopia Rural Socioeconomic Survey (ERSS) panel data collected in the years 2011/12, 2013/14, and 2015/16. Figure 2.1 shows the locations of the sample households based on the GPS (longitude and latitude) coordinates of their communities (enumeration areas).[7] We merged the ERSS data to an objective measure of drought shocks with 0.5 degrees spatial resolution that is made available by the University of East Anglia Climatic Research Unit (UEA-CRU)[8].

labour market. Therefore, expected returns are based on anticipated future financial support such as private transfers at old age.

[6] Glewwe and Miguel (2007) highlight that child health can directly affect schooling outcomes.

[7] In order to maintain confidentiality of respondents, the GPS coordinates of sampled communities where the households reside are presented in the panel data.

[8] The database is available at: `http://sac.csic.es/spei/database.html`

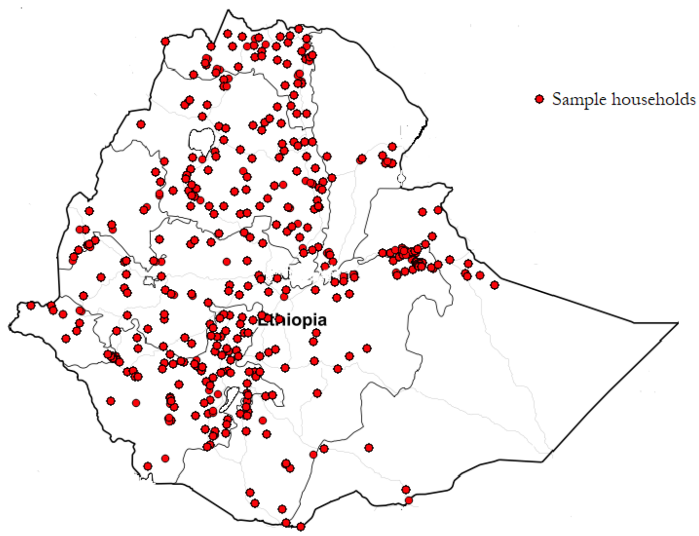


Figure 2.1: Sample households observed in all survey rounds

We use strongly balanced individual-level panel data from 3,639 households in 332 communities. Table 2.1 summarises the number of households and school-age children (i.e. between 7 and 18 years of age in 2011/12) that are present in all survey rounds. Accordingly, we conduct all of our econometric analyses on panel data that consist of 5,667 children that were between 7 and 18 years of age in the first wave and observed in the subsequent two survey waves – resulting in a total of 17,001 observations.

Table 2.1: Number of households and children in each survey rounds

	2011/12	2013/14	2015/16
Interviewed (tracked) households	3,969	3,776	3,639
Observed (tracked) school-age children	5,900	5,769	5,667

Notes: Between the initial and last survey waves, only 233 school-age children could not be tracked.

The choice of the lower and upper bounds for the age range to be 7 and 18 years is based on Ethiopia's officially deemed proper age for a child to enrol to primary school (start first grade) and complete high school (complete grade 12), respectively. The use of 7 years as the lower age bound is also justified in our data since the education outcomes for children below the age of 7 years are missing in the initial survey wave (2011/12). The choice of a wider upper bound (i.e. 18 years) is to accommodate a common scenario in rural Ethiopia where there is a high possibility for late (delayed) entry to school and grade repetition. UNESCO's 2012 report presents similar facts indicating that 20 percent of children enrolled in primary education in Ethiopia are overage for their grades. Consequently, we encountered plenty children that can be considered over-age for their grades. Figure 2.2 demonstrates this by depicting age distribution and the highest grade completed of our sample children that are enrolled to school for the 2011/12 academic year. During that year, more than 90 percent of those children who are between 15 and 18 years of age were attending primary school – 35 percent 1^{st} cycle (grades 1 to 4) and 56 percent 2^{nd} cycle (grades 5 to 8). Overall, 23 percent of the primary school going children are above the intended primary school age (i.e. they are 15 years and above). Incidences of children's age and sex misreporting are corrected by matching the accuracy of the registered age and sex information in the household roster with the verification questions, which entail information on the correct sex and age of the child, in the 2013 survey round.

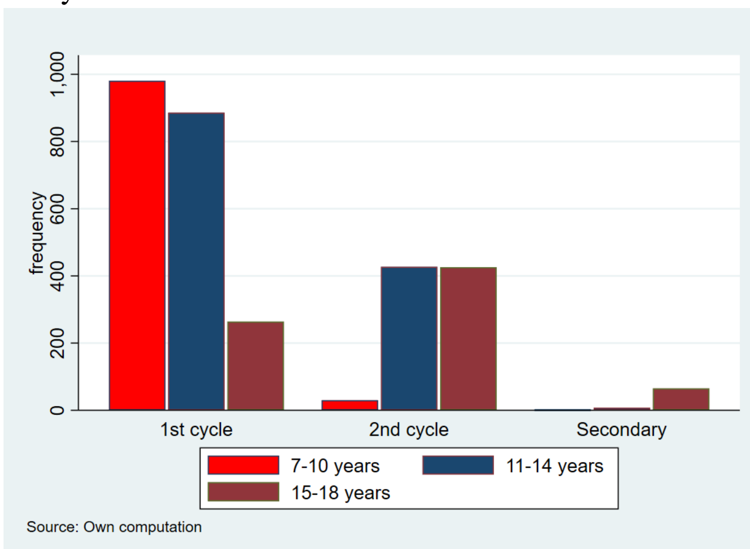


Figure 2.2: Age distribution and grade completed for enrolled school-age children in 2011/12

Note: 1^{st} and 2^{nd} cycles are grades 1-4 and 5-8, respectively. Secondary school comprises grades 9-12.

2.3.2 Main variables of interest

This section describes the outcome and explanatory variables of interest. The description and descriptive statistics on the child health and schooling variables, measure of drought shocks, and child, household and community characteristics for the pooled data are presented in Appendix Table A2.3.

School outcomes

The outcome variables are for children between 7 and 18 years of age in 2011/12 and observed in 2013/14 and 2015/16 survey rounds (see section 4.1). School absenteeism and completed years of schooling are common measures of child education (see Smerillo et al. (2018) and other references therein). Due to lack of objectively measured child schooling outcome indicators in the panel data set, our study utilizes self-reported school absenteeism and highest grade completed. Related studies by Björkman-Nyqvist (2013) and Randell and Gray (2016) also use self-reported measures of child schooling.

(a) School absenteeism: is a binary variable taking the value of 1 if the child was absent from school for more than a week in the past month during the survey year, and zero otherwise. Appendix Table A2.3 shows that conditional on school enrolment, on average, 10 percent of children skip classes for more than a week during the last month in each survey round.

(b) Highest grade completed: is a count variable indicating the highest grade the child completed during the survey year. The highest completed formal years of schooling are on average 3.2 years during the span of the panel survey period (2011/12-2015/16).

Child health and medical treatment

Similar to child schooling indicators, we use self-reported child health status as the panel data do not include an objective measure of child health using laboratory tests and screens. Related studies by Jensen (2000) and Aturupane et al. (2013) also used self-reported child health status in their analyses. Reported illness takes the value of 1 if a child between 7 and 18 years of age faced illness during the last 2 months in the survey year, and 0 otherwise. Conditional on illness, our "medical treatment" variable is binary taking the value of 1 if the ill child gets medical attention (treatment), and 0 otherwise. Furthermore, conditional on untreated illness, we also have a binary variable named inability to pay for medical treatment that takes the value of 1 if the household responded "lack of money" or "it is expensive" as a reason for not taking a child to medical treatment during illness, and 0 otherwise. During the panel survey period, on average, illness occurred among 10 percent of the sample children.[9] Out of these, 68 percent received medical treatment. Concerning the untreated children, around 40 percent of them do not receive medical treatment due to liquidity constraints of the households (Appendix Table A2.3).

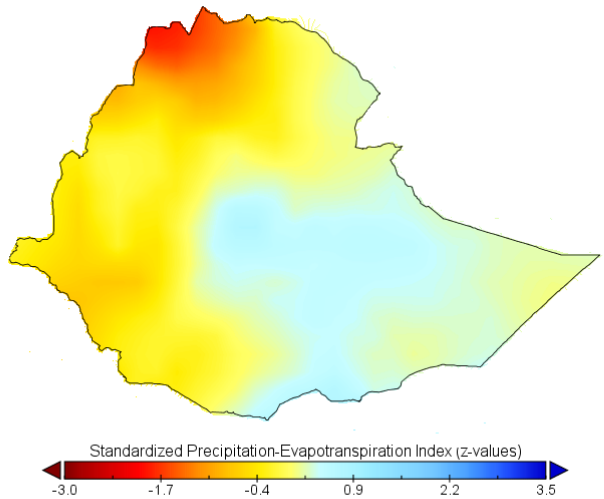
Drought shock

Our drought shock variable is the standardized precipitation evapotranspiration index (SPEI), which is a multiscalar measure of drought pioneered by Vicente-Serrano et al. (2010). SPEI is computed by integrating the best qualities of the Palmer Drought Severity Index (PDSI) and the Standardized Precipitation Index (SPI) to capture deviations in total precipitation and temperature from historical means.[10] The use of such relative measure, instead of an absolute measure of rainfall and temperature, is preferable because the same amount of rainfall and temperature may have different consequences in different regions based on variations in agro-ecologies. The SPEI values are calculated on time scales between 1 and 48 months. Between January and December, the agricultural production year in Ethiopia is divided into two production seasons, belg and meher.[11] In the context of Ethiopia, negative deviations have serious repercussions on household income.

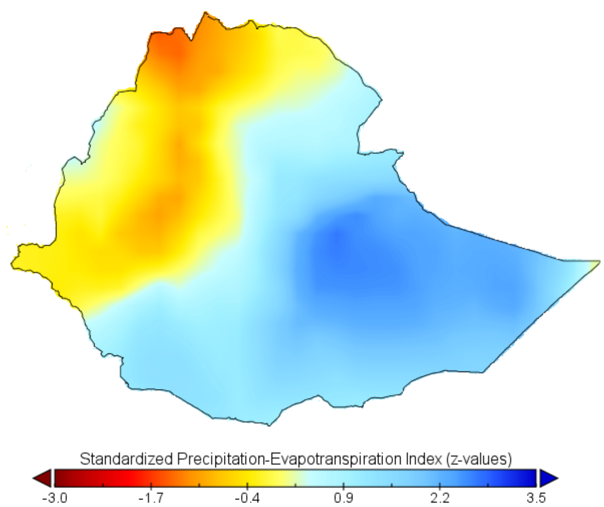
[9] This is based on the total number of reported child illness in all survey waves.

[10] The global SPEI database offers the SPEI values for the period between January 1901 and December 2015.

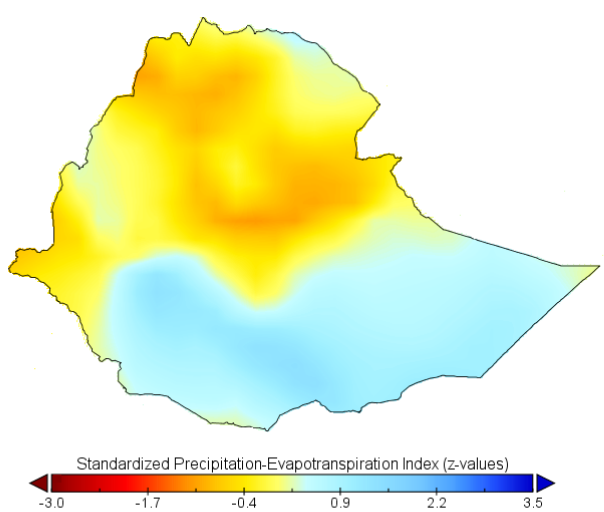
[11] *Belg* is the short rainy season that extends from March and early May. *Meher* is the main agricultural season extending between June and September.



(a) SPEI values in 2011



(b) SPEI values in 2013



(c) SPEI values in 2015

Figure 2.3: SPEI values at the time scale of 12 months for the years 2011, 2013 and 2015

Shiferaw et al. (2014) and Adhikari et al. (2015) show that recurrent and sometimes prolonged droughts are the major risk for the countries of the Sahel, the Greater Horn and Southern Africa. Our objective drought variable is measured using SPEI values that are constructed based on a time scale of 12 months for the months January-December of the survey year. The SPEI for each survey year is merged with the individual-level data using the longitude and latitude coordinates of the community (enumeration area) of the sample household where the child resides. The maps in Figure 2.3 show that drought shocks occur in all the three survey years, but vary in magnitude and spatial coverage. Moreover, as Appendix Figure A2.1 presents, the distribution of SPEI values varies across regions of Ethiopia and drought shocks are highly regionally correlated. Tigray, Amhara, Benshangul Gumuz, and Gambela regions have experienced negative deviations – drought shocks – for the entirety of the panel survey years. However, a histogram plot for the distribution of climate shocks of the pooled data shows that SPEI values for the whole sample of children are randomly distributed and clustered around the mean value of 0.11 (Appendix Figure A2.2). Therefore, looking at the pooled distribution of climate data alone may give a wrong impression of having a randomly distributed climate variable for all sample study areas.

The drought shock variable for our analyses is left-bounded at zero and obtained by multiplying the SPEI by (-1) if the values are negative, which indicate drought shock.[12] While the average magnitude of drought for all survey rounds is greater than zero, the years 2011/12 and 2015/16 registered the highest and almost identical average magnitude of drought shock during the panel survey period. This reflects the frequency of severe drought shocks in the country.

$$Drought\ shock = \begin{cases} \text{SPEI} \times (-1) & \text{if SPEI} < 0 \\ 0 & \text{if SPEI} \geq 0 \end{cases}$$

Our climate shock variable is exogenous only if households do not self-select into or out of experiencing drought. In this respect, attrition is a major challenge if the missing households were more or less exposed to drought. Household attrition rate is low (8 percent between the first and the third survey rounds), and not systematically related to exposure to drought shocks (Appendix Table A2.1). In addition, we examine whether attrition among children co-varies with child demographic and human capital variables – they do not (Appendix Table A2.2).

2.3.3 Control variables

Appendix Table A2.3 presents child and household level control variables that are included in our panel data regression models. These control variables capture: (a) demographic characteristics of the child, and (b) demographic and socioeconomic characteristics including proxies for wealth and access to markets, basic services, and infrastructure of the household that the child resides.

[12] Multiplying the negative deviations by -1 would ease the interpretation of the parameter estimates on our drought measure. Hence, higher values indicate higher magnitude of drought.

2.4 Identification Strategy

Equation 2.1 relates H_{it}^{*} – a child's propensity to get ill where we only observe a binary reported child illness – to time-varying drought shock (D_{ct}) after adjusting for the effects of observed heterogeneities such that $X_{it} = \{X_{1it}, X_{2it}\}$. Similarly, Equation 2.2 is a linear representation of the latent schooling variable (S_{it}^{*}) for our observed (either binary or count) schooling outcomes. μ_i is child-level time-invariant unobserved heterogeneities and ε_{it} is independent and identically distributed (i.i.d) error term.

$$H_{it}^{*} = \beta_1 D_{ct} + \delta_1 X_{it} + \mu_{1i} + \varepsilon_{1it} \tag{2.1}$$

$$S_{it}^{*} = \beta_2 D_{ct} + \delta_2 X_{2it} + \mu_{2i} + \varepsilon_{2it} \tag{2.2}$$

where the subscripts indicate variation over children (i = 1, 2, ..., N) in communities (c=1, 2, ...,C) over time (t = 1, 2, ..., T).

The coefficient of drought (β) can be estimated using pooled regressions by clustering the composite error terms ($\omega_{it} = \mu_i + \varepsilon_{it}$) at the community level. Cluster-robust pooled estimations result in heteroskedasticity-consistent standard errors by relaxing the assumption of i.i.d errors (Wooldridge, 2010; Millo, 2017) for a child across time and between children within a community.[13] Related empirical studies used cross-sectional variations (Bauer and Mburu, 2017) or district fixed effects (Björkman-Nyqvist, 2013; Randell and Gray, 2016) methods to estimate the effect of climate shocks on either child health or education outcomes. However, a causal inference based on the parameter estimates of a climate shock variable after using cross-sectional variation estimators can only be made if the shock is randomly determined at the individual-level (Di Falco and Vieider, 2018). In this respect, the assumption that all communities (and children therein) have the same probability of experiencing drought regardless of their regional location is not satisfied in our data (Appendix Figure A2.1) despite climate shocks being exogenous[14] and random on average for the whole population in Ethiopia (Appendix Figure A2.2). Moreover, community or district fixed effects would not account for child- and household-level unobserved time-invariant heterogeneities that may enhance or mitigate the effect of climate shocks. We, therefore, rely on the within-child variation estimators as our preferred estimation strategy, instead of cross-sectional variations or community fixed effects, for identifying the impact of drought shock on the outcome variables of interest.[15]

The hybrid model splits within- and between-variation estimates for the time-varying variables (Alison, 2009; Schunck and Perales, 2017). Equations 2.3 and 2.4 transform equations 2.1 and

[13] In the context of panel data with binary dependent variable, Wooldridge (2010) advocates the use of a partial MLE procedure of a pooled probit model using cluster-robust standard errors. The parameter estimates and the cluster-robust standard errors are consistent under the assumption that the variable of interest is exogenous.

[14] We showed that attrition in our panel data is random and thus drought shocks are exogenous to the households (Appendix Table A2.1).

[15] (Di Falco and Vieider, 2018) show the merits in relying on within-individual variation (individual fixed effect) estimation for causal inference when one cannot guarantee idiosyncratic climate shocks across individuals and a uniformly distributed dependent variable prior to the shocks.

2.2, respectively, into the hybrid model by including both the deviations from panel-specific means ($D_{ct} - \overline{D}_c$) and the panel-specific means ($\overline{D}_c$) instead of the original drought measure (D_{ct}).[16] The same holds for the remaining time-varying control variables.

$$H_{it} = \alpha_1 + \beta_3(D_{ct} - \overline{D}_c) + \beta_4\overline{D}_c + \delta_3(X_{it} - \overline{X}_i) + \delta_4\overline{X}_i + v_{1i} + \varepsilon_{3it} \tag{2.3}$$

$$S_{it} = \alpha_2 + \beta_5(D_{ct} - \overline{D}_c) + \beta_6\overline{D}_c + \delta_5(X_{2it} - \overline{X}_{2i}) + \delta_6\overline{X}_{2i} + v_{2i} + \varepsilon_{4it} \tag{2.4}$$

where β_3 and β_5 are the within-child effect estimates of drought, our parameters of interest. β_4 and β_6 are between-child effect estimates of the shock.[17] v_i and ε_{it} are time-invariant and time-varying child-level error terms, respectively.

Moreover, in the face of climate shocks, we pose a question on the assumption of independence between the contemporaneous child health and education that the existing empirical studies impose for identification reasons – endogenous child health status. Child health and education may not be independent in the short-run. Thus, the effect of drought on child schooling may also be channelled through its effects on health. Following the discussion by MacKinnon et al. (2012) and Hayes (2017) on the approaches to total and mediation effect analyses, equations 2.3 and 2.4 represent formal econometric models for total effect estimations. Equation 2.5 is the mediation analysis that relates drought and schooling outcomes taking child health as having an indirect (a mediating) effect. Any correlation between the child health and time-invariant unobserved heterogeneities (μ_i) is captured by including panel-specific means of child illness and other time-variant variables in child schooling model (equation 2.5).[18]

$$\begin{aligned} S_{it} = &\alpha_3 + \beta_7(D_{ct} - \overline{D}_c) + \beta_8\overline{D}_c + \theta_1(H_{it} - \overline{H}_i) + \theta_2\overline{H}_i + \\ &\delta_7(X_{2it} - \overline{X}_{2i}) + \delta_8\overline{X}_{2i} + v_{3i} + \varepsilon_{5it} \end{aligned} \tag{2.5}$$

where the within-child variation estimate (θ_1) captures the effect of health status on schooling outcomes of a given child after adjusting for the endogeneity that arises due to time-invariant heterogeneities.

As our preferred technique, we estimated the within- and between-cluster (child) effects of the variables of interest in a single model (equations 2.3-2.5) using probit and poisson estimators for the binary and count dependent variables, respectively. In this approach, the child-specific time-invariant and time-varying error terms in the equations are combined as: $\omega_{it} = v_i + \varepsilon_{it}$. The main advantage of this approach is that we can compute the average marginal effects (AMEs), which are easy to interpret and understand. As a robustness check, we also use the multilevel mixed-effects

[16] While the deviations from panel-specific means captures within-panel variation (fixed effect) estimates, the panel-specific means are between-panel (cross-sectional) variation estimates (Schunck and Perales, 2017).

[17] In panel-data analysis, it is questionable whether the between-cluster effects (cross-sectional variations) are of substantial interest at all since the interest lies mainly on the within-cluster effects (Schunck and Perales, 2017; Di Falco and Vieider, 2018).

[18] This approach was initially proposed by Mundlak (1978) and further extended by Chamberlain (1980, 1982) to allow unobserved time-invariant heterogeneities to be correlated to the explanatory variables. This is achieved by modelling the time-invariant disturbance as a linear projection onto the panel-specific means of time-variant variables, such that: $\mu_i = \alpha + \theta\overline{H}_i + \delta\overline{X}_i + v_i$.

generalized linear model (meglm) to account for the presence of the separate time-invariant and time-varying i.i.d error terms. All our estimations are undertaken separately for the whole sample, female children, and male children.[19] The error terms are clustered at the community level to allow for serial and spatial correlations.

A serious concern with the within-variation estimators is the possible endogeneity that may arise from the correlation between time-varying unobserved heterogeneity (ε_{it}) and child illness, which may bias our parameter estimate (θ_1) in equation 2.5. Moreover, within-variation estimators may also suffer from simultaneity bias (reverse causality). For instance, education may equip children with disease prevention attitude and hence may enable them to avoid illness. Therefore, we use a maximum likelihood estimator of a binary or continuous outcome with a binary endogenous regressor under the recursive bivariate analysis, as proposed by (Maddala, 1983), to improve causal inference on the effect of child health on schooling outcomes. The binary reported child illness variable is an endogenous regressor in the equation determining the child's schooling outcomes. In this specification, child health can be correlated to both time-invariant and time-varying heterogeneities while taking into account the non-independence among children in the same community.

The real challenge of the approach is finding an instrumental variable that satisfactorily addresses both the statistical and conceptual scrutiny. Drawing on medical and public health literature, improved hygiene and sanitation facilities have strong and consistent impact on health outcomes. Evidence from randomized control trials and observational research shows reasonably strong and consistent impacts of hygiene and sanitation interventions on the incidences of contagious diseases such as diarrhoea, parasitic worms and other infections including trachoma, influenza and rhinorrhoea (see recent reviews by Freeman et al. (2017), and McMichael (2019)). Previous studies also show that the effects of improved hygiene and sanitation facilities on child education are channelled through their effects on child health. Children with access to better hygiene and sanitation conditions in their schools are less likely to dropout out of school due to illness (Talaat et al., 2011; Trinies et al., 2016) and they are more likely to attain better cognitive learning and learning performance in the long-term (Ezeamama et al., 2018). We, therefore, employ the proportion of children that have access to improved toilet facilities[20] in the community as the excluded variable (X_{1it}) from the educational outcomes model specification. Aturupane et al. (2013) also use children's access to a toilet facility as an instrumental variable to measure the effect of child health on education performance. We test the admissibility of our instrument – whether the improved toilet facility embodies an exogenous source of variation affecting only child health but not education outcomes – using a simple falsification test suggested by Di Falco et al. (2011). Accordingly, the proportion of children in the community that have access to improved toilet facilities should not be a significant determinant of non-ill children's education.

[19] We used Wald chi-square to examine whether coefficients differ across gender.

[20] Improved toilet (sanitation) facilities include: flash toilet (private or shared), pit latrine ventilated (private or shared), pit latrine (private or shared) with slub, and composting toilet (private or shared). Sanitation classifications as improved or unimproved are based on those defined by the WHO/UNICEF Joint Monitoring Programme (JMP), which is available at: `http://www.who.int/water_sanitation_health/publications/jmp-2017/en/`.

2.5 Results and Discussion

In the subsequent sections, we provide point estimates on the impact of drought on child human capital based on within-child variation estimators.[21] We also explore potential channels that may explain the observed relationship between drought and human capital of children.

2.5.1 Impact of drought on child schooling

Table 2.2 presents the total effect of a drought on contemporaneous child schooling outcomes. Regardless of gender, drought shock has a positive impact on school absenteeism, but the within child estimates are not statistically significant in any of the specifications (columns 1 and 2). We introduce an interaction term between age of the child and magnitude of drought (columns 3 and 4) to explore variations in the relationship between climate shocks and school attendance for a unit change in the age of the child. We find a statistically significant positive within-child effect of drought on school absenteeism of older female children. For a given female child, the effect of drought on the odds of school absenteeism increases by 20 percent for a year increase in her age. A study by Björkman-Nyqvist (2013) in Uganda also shows that the adverse effect of negative deviations in rainfall on children's probability of going to school grows stronger for older girls.

We also find evidence on the negative within-child impact of drought on the highest grade completed in both panel models (Table 2.2 columns 5 and 6). For a given child, a one standard deviation increase in drought shock – a unit standard deviation decrease in SPEI for values less than 0 – results in decline in the expected count of grade attainment by 0.18. The negative effect of drought on a female child's highest completed formal school years is stronger in magnitude and robust under alternative panel model specifications. An increase in the magnitude of drought disproportionately affects a female child's human capital by lowering her expected count of highest completed formal school years on average by 0.25 – a 6 percent decrease based on meglm model. Hence, in the context of SSA, the impacts of drought on child schooling via its income effects are gender-specific where female children bear the brunt of climate change.

Figure 2.4 presents the relationship between the predicted probability of school absenteeism of children and the magnitude of drought after running a probit model on equation 2.4. The probability of a given child's absenteeism increases with an increase in the magnitude of drought. This relationship is slightly stronger for male children (Panel a). However, when we add the age dimension besides gender, the within-child effect of drought is much stronger for older female children (Panel b). Figure 2.5 plots predicted completed school years against within-child variations in the magnitude of drought after linear regression. Accordingly, for a given child, the magnitude of drought and the highest grade completed have a stronger inverse relationship for female children, as shown by a steeper slope.

[21] For brevity and the identification reasons presented in section 5, we only interpret and discuss the within-child effect estimates. As our preferred estimators, we use probit and poisson models for the binary and count dependent variables, respectively, to estimate the within- and between-cluster (child) effects of the variables of interest in a single model.

Table 2.2: The impact of drought shock on child schooling

	(1) Absenteeism		(2) Absenteeism	(3) Absenteeism	(4) Grade comp.		(5) Grade comp.
variables	Probit (Coeff.)	Probit (AME)	meglm-Logit	meglm-Logit	Poisson (Coeff.)	Poisson (AME)	meglm-Poisson
A. All Children							
drought (within effect)	0.0834	0.0139	0.1164	-1.5527**	-0.0554***	-0.1764***	-0.0502**
	(0.1259)	(0.0210)	(0.2564)	(0.6840)	(0.0206)	(0.0652)	(0.0213)
droughtXage (within effect)				0.1355**			
				(0.0569)			
drought (b/n effect)	0.7280***	0.1213***	1.2019***	0.8079	-0.0559	-0.1780	-0.1020
	(0.1887)	(0.0322)	(0.3078)	(0.6086)	(0.0901)	(0.2870)	(0.1007)
droughtXage (b/n effect)				0.0305			
				(0.0448)			
constant	-1.7882***		-3.2456***	-3.0869***	-0.6381***		-0.8589***
	(0.2251)		(0.4102)	(0.4413)	(0.1043)		(0.1311)
Observations	9,795	9,795	9,795	9,795	14,595	14,595	14,595
B. Female Children							
drought (within effect)	0.0701	0.0115	-0.0113	-2.1875**	-0.0816***	-0.2540***	-0.0588**
	(0.1383)	(0.0227)	(0.2973)	(0.9784)	(0.0293)	(0.0910)	(0.0287)
droughtXage (within effect)				0.1824**			
				(0.0829)			
drought (b/n effect)	0.7355***	0.1208***	1.3062***	0.9429	0.0648	0.2018	0.0056
	(0.1995)	(0.0332)	(0.3202)	(0.8911)	(0.0935)	(0.2907)	(0.1067)
droughtXage (b/n effect)				0.0292			
				(0.0666)			
constant	-1.5669***		-2.9474***	-2.8143***	-0.6195***		-0.7882***
	(0.2637)		(0.4705)	(0.5483)	(0.1238)		(0.1558)
Observations	4,706	4,706	4,706	4,706	6,801	6,801	6,801

Table 2.2: Continued

	(1) Absenteeism		(2) Absenteeism	(3) Absenteeism	(4) Grade comp.		(5) Grade comp.
variables	Probit (Coeff.)	Probit (AME)	meglm-Logit	meglm-Logit	Poisson (Coeff.)	Poisson (AME)	meglm-Poisson
C. Male Children							
drought (within effect)	0.0797	0.0132	0.1937	-0.8993	-0.0345	-0.1120	-0.0433*
	(0.1447)	(0.0241)	(0.2981)	(0.8208)	(0.0273)	(0.0885)	(0.0257)
droughtXage (within effect)				0.0863			
				(0.0629)			
drought (b/n effect)	0.7405***	0.1230***	1.1248***	1.1666	-0.1541	-0.5007	-0.2015
	(0.2237)	(0.0378)	(0.3801)	(0.7302)	(0.1113)	(0.3602)	(0.1284)
droughtXage (b/n effect)				-0.0030			
				(0.0536)			
constant	-1.9689***		-3.4275***	-3.4216***	-0.6811***		-0.9434***
	(0.2796)		(0.5445)	(0.5730)	(0.1204)		(0.1498)
Observations	5,089	5,089	5,089	5,089	7,794	7,794	7,794
Chisquare		78.76***				106.65***	

Robust standard errors in parentheses: Clustered at community level.

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

All estimations include control variables − child and household characteristics, and region and survey year dummies (Appendix Table A2.3) − but the results for these variables are not reported for brevity.

AME stands for average marginal effect.

We used a Stata command written by Schunck and Perales (2017) for the meglm regressions.

The interaction effect between drought and child age is interpreted in the main text as exponentiated coefficient, odds ratio, of the interaction term in column 3. In this regard, Buis (2010) shows that odds ratios render an attractive alternative to interpreting interaction effects without referring to any additional program.

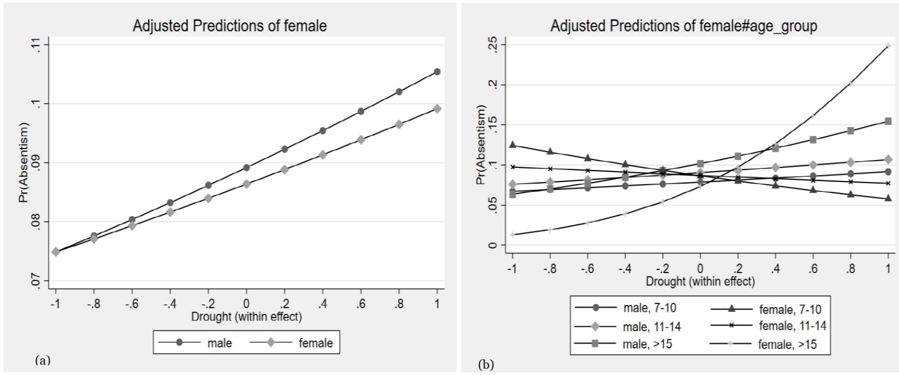


Figure 2.4: Relationship between school absenteeism and drought

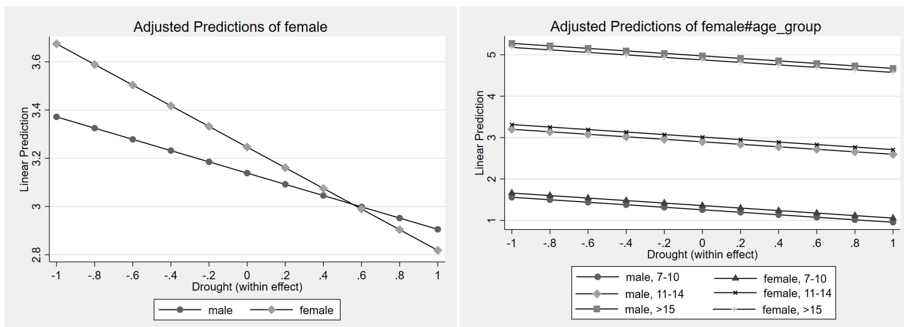


Figure 2.5: Relationship between highest grade completed and drought

2.5.2 Impact of drought on reported child illness

The binary reported child illness variable captures whether the child faces illness in the past two months during the survey period. Table 2.3 shows that reported illness significantly increases with the increase in the magnitude of drought. The within-child variation analysis in Panel A column 1 shows that, on average, reported child illness increases by around 4 percentage points for an increase in the magnitude of drought.

The within-effect estimate of drought on child illness remains robust under meglm model specification. Accordingly, for a given child, the odds of illness (relative to non-illness) are more than 50 percent higher for a standard deviation increase in the magnitude of drought (Table 2.3 Panel A columns 2). As shown in Panels B and C of the same Table, the health impact of drought is statistically significant and robust regardless of gender. However, the impact is more notable among female children as the effect for males is only significant at 10% level. Moreover, contrary to school attendance, the within-child effect of drought on child health does not vary based on age (columns 3 and 4).

Table 2.3: The effect of drought shock on reported child illness

	(1) Child illness (Probit)		(2) Child illness	(3) Child illness (Probit)		(4) Child illness
variables	Coeff.	AME	meglm-Logit	Coeff.	AME	meglm-Logit
A. All Children						
drought (within effect)	0.2230**	0.0363**	0.4331**	0.2285	0.0371	0.2394
	(0.0886)	(0.0144)	(0.1854)	(0.2245)	(0.0366)	(0.4822)
droughtXage (within effect)				-0.0002	-0.0000	0.0156
				(0.0160)	(0.0026)	(0.0340)
drought (b/n effect)	0.6945***	0.1130***	1.3285***	0.2581	0.0419	0.8036
	(0.1348)	(0.0219)	(0.2375)	(0.2803)	(0.0455)	(0.5588)
droughtXage (b/n effect)				0.0327*	0.0053*	0.0387
				(0.0174)	(0.0028)	(0.0343)
constant	-1.6693***		-3.2149***	-1.5343***		-3.0420***
	(0.1786)		(0.3465)	(0.1907)		(0.3735)
Observations	14,680	14,680	14,680	14,680	14,680	14,680
B. Female Children						
drought (within effect)	0.2335**	0.0397**	0.4750**	0.0114	0.0019	-0.2417
	(0.1095)	(0.0186)	(0.2230)	(0.3090)	(0.0526)	(0.6628)
droughtXage (within effect)				0.0173	0.0029	0.0569
				(0.0225)	(0.0038)	(0.0492)
drought (b/n effect)	0.4821***	0.0820***	0.9047***	0.3619	0.0616	1.0361
	(0.1760)	(0.0297)	(0.2935)	(0.3809)	(0.0645)	(0.7152)
droughtXage (b/n effect)				0.0097	0.0017	-0.0090
				(0.0262)	(0.0045)	(0.0468)
constant	-1.5445***		-2.8613***	-1.5069***		-2.8880***
	(0.2371)		(0.4468)	(0.2508)		(0.4821)
Observations	6,840	6,840	6,840	6,840	6,840	6,840
C. Male Children						
drought (within effect)	0.2165*	0.0336*	0.3977*	0.4359	0.0675	0.5696
	(0.1114)	(0.0173)	(0.2414)	(0.3229)	(0.0502)	(0.6752)
droughtXage (within effect)				-0.0157	-0.0024	-0.0117
				(0.0227)	(0.0035)	(0.0469)
drought (b/n effect)	0.8709***	0.1350***	1.7289***	0.2456	0.0380	0.8172
	(0.1364)	(0.0218)	(0.2659)	(0.3261)	(0.0506)	(0.6820)
droughtXage (b/n effect)				0.0455**	0.0070**	0.0659
				(0.0203)	(0.0031)	(0.0419)
constant	-1.8665***		-3.7197***	-1.6725***		-3.4214***
	(0.1970)		(0.4122)	(0.2191)		(0.4567)
Observations	7,840	7,840	7,840	7,840	7,840	7,840
Wald chi-square	37.61			39.70		

Robust standard errors in parentheses: Clustered at community level. $***p < 0.01, **p < 0.05, *p < 0.1$

All estimations include control variables listed in Appendix Table A2.3. AME stands for average marginal effect.

We used a Stata command written by Schunck and Perales (2017) for the meglm regressions.

2.5.3 Impact pathways

In this section, we investigate individual within-household allocation and use of resources in the face of drought to explain its impacts on human capital of children. As explained in section 2.2, intrahousehold food allocation, health care and education expenditures, and labour use are potential pathways through which climate shocks may affect child health and schooling. The ERSS panel data have individual-level information on self-reported illnesses and healthcare-seeking behaviour. The data also have information on individual-level labour utilization within a household for domestic, productive and paid activities. However, food consumption and education expenditures are aggregates at the household level. Therefore, we explore the impact pathways making use of these individual- and household-level variables as follows.

(a) Pathways for impacts on child illness

Food consumption: As explained by (Gundersen and Ziliak, 2015), climate shocks can negatively affect child health through the effects on food and nutrition security. Households experiencing drought shocks may employ consumption destabilizing coping responses by lowering the quantity and quality of meals (Brown and Funk, 2008; Saronga et al., 2016). Low food availability, access, and utilisation during drought periods may consequently induce child illness. Unfortunately, we do not have information on individual-level food consumption for school-aged children to verify this mechanism. Instead, we rely on household-level analysis to examine the impact of drought on food consumption expenditure and the average number of meals taken per day across time. Based on our investigation using within-household variation estimators, we find no evidence that suggests drought has an effect on food consumption expenditure and behaviour for a given household (Appendix Table A2.4). We also use within-child variation estimation to examine the impact of drought on height-for-age, an indicator of overall nutritional status, of children that aged 3 years and below in 2013/14 survey round, and assess intrahousehold variations in the allocation of food.[22] Appendix Table A2.5 presents that drought significantly increases a child's probability of being stunted regardless of sex of the child.[23] Food and nutrition insecurity of children are major factors that lead to poor health outcomes (Gundersen and Ziliak, 2015). The other plausible channel for the impact of drought on child health is through its effect on the health environment. Drought creates a conducive environment for widespread occurrences of vector-borne, water-borne, and infectious diseases (Bunyavanich et al., 2003; Lafferty, 2009; Stanke et al., 2013).

Intra-household resource allocation for child health care: We now explore household-level decisions concerning the allocation of resources to health care services in the face of drought-induced

[22]Despite the analysis is on other age group than the analytical sample of the study, this exercise assesses the nutritional impact drought in rural households. Therefore, it should be noted that food allocation decisions based on sex of the child may vary across various age groups.

[23]Low height-for-age (stunting) is a major public health problem with long-term effects on individual health and educational outcomes (Dewey and Begum, 2011).

Table 2.4: Impact of drought on medical treatment and inability to pay for treatment

	(1)		(2)	(3)	
	Med. treat.		Med. treat.	Inability to pay	
variables	Coeff.	Probit (AME)	meglm-Logit	Coeff.	Probit (AME)
A. All Children					
drought (within effect)	0.2917	0.0947	1.5271**	0.5851	0.1883
	(0.2251)	(0.0726)	(0.6467)	(0.4561)	(0.1437)
drought (b/n effect)	0.4802**	0.1559**	0.6516*	0.4131	0.1329
	(0.2433)	(0.0789)	(0.3374)	(0.3960)	(0.1279)
constant	-0.6095*		-0.6189	-1.4248**	
	(0.3669)		(0.6369)	(0.6843)	
Observations	1,410		1,410	405	
B. Female Children					
drought (within effect)	0.0117	0.0037	0.3562	1.0838*	0.3181*
	(0.2289)	(0.0733)	(0.7303)	(0.6059)	(0.1712)
drought (b/n effect)	0.8032**	0.2571**	0.8801*	0.7334	0.2153
	(0.3308)	(0.1053)	(0.4975)	(0.6438)	(0.1892)
constant	-0.9577*		-1.1640	-1.9288**	
	(0.4930)		(0.9768)	(0.9724)	
Observations	694		694	206	
C. Male Children					
drought (within effect)	0.5616*	0.1843*	2.7161***	0.1840	0.0538
	(0.3305)	(0.1074)	(0.8987)	(0.5755)	(0.1681)
drought (b/n effect)	0.3709	0.1217	0.5946	0.0012	0.0004
	(0.3152)	(0.1030)	(0.3990)	(0.4690)	(0.1373)
constant	-0.3818		-0.0415	-0.7389	
	(0.4910)		(0.8359)	(1.0384)	
Observations	716		716	199	
Wald chi-square	45.07			64.89***	

Robust standard errors in parentheses: Clustered at community level.

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

All estimations include control variables listed in Appendix Table A2.3.

AME stands for average marginal effect.

We used a Stata command written by Schunck and Perales (2017) for the meglm regressions.

income shocks. Our assessments on the gender-disaggregated impact of drought on households' decision to seek medical treatment during child illness and inability to pay for treatment reveal that there is a gender bias in the allocation of resources for health care, with female children being worse-off. Table 2.4 Panel C shows that for an increase in the magnitude of drought, a given male child is more likely to get medical treatment conditional on illness. On the contrary, conditional on illness, a given female child has no chance of getting medical attention with an increase in the severity of drought (Table 2.4 Panel B columns 1 and 2). Moreover, among the untreated children, the probability that an ill female child does not receive medical treatment due to household's liquidity constraints increased by 32 percentage points for a unit standard deviation increase in the magnitude of drought (Table 2.4 Panel B column 3). Our results show that female children are disfavoured by the intra-household resource allocation to health care in the presence of climate shocks. As such, while male children are protected, households tend to divert health care spending away from female children as a coping response to drought-induced income shocks.

(b) Pathways for impacts on child education

Contemporaneous link between child health and education: In this section, we examine the possible contemporaneous link between education and drought-induced ill health of children to deepen our understanding of the short-run climate shocks-human capital nexus. This also allows us to examine the income effect of drought on child education through health and the extent to which this effect varies due to gender bias in households' coping responses. The seemingly unrelated multivariate analysis reported in Appendix Table A2.6 shows that the equations for health (equation 2.3) and education (equation 2.4) are not independent after adjusting for the effects of drought shock and other control variables. The correlation parameters (ρ) provide evidence for the presence of statistically significant dependence between children's health (as measured by reported child illness), and schooling outcomes – absenteeism and highest grade completed – in the expected direction. In particular, the correlation between health status and highest grade completed is statistically significant only for female children. We conducted further gender-disaggregated analyses to directly examine child illness as a mediating factor using within-child variation estimators.

Table 2.5 shows that child illness significantly reduces school attendance and the highest grade completed after adjusting for the direct effect of drought and the effects of other observed and unobserved confounders. On average, child illness increases the probability of school absenteeism of both a female and male child by 15 and 12 percentage points, respectively. In the meglm models, on average, the odds of school absenteeism is around 5 times higher for a female child and around 4 times higher for a male child for an increase in the magnitude of drought. Child illness also has a negative effect on completed formal school years for both sexes. In terms of magnitude, however, the negative effect of illness on the expected number of count on the highest grade completed of a given female child is twice as large as its effect on a male's child (Columns 3 and 4 in Panels B and C). This implies that, on average, a female child is twice as likely to lag behind in her grade

Table 2.5: Mediation analysis − the effect illness on schooling in the presence of drought

	(1) Absenteeism		(2) Absenteeism	(3) Grade comp.		(4) Grade comp.
variables	Coeff.	AME	meglm-Logit	Coeff.	AME	meglm-Poisson
A. All Children						
illness (within effect)	0.8583***	0.1376***	1.6423***	-0.0675***	-0.2151***	-0.0595***
	(0.0809)	(0.0130)	(0.1806)	(0.0189)	(0.0602)	(0.0172)
drought (within effect)	0.0412	0.0066	0.0355	-0.0516**	-0.1643**	-0.0463**
	(0.0904)	(0.0145)	(0.2722)	(0.0206)	(0.0652)	(0.0212)
illness (b/n effect)	0.6422***	0.1030***	1.4122***	-0.0182	-0.0578	0.0065
	(0.0979)	(0.0157)	(0.1856)	(0.0533)	(0.1698)	(0.0707)
drought (b/n effect)	0.6546***	0.1049***	1.0594***	-0.0543	-0.1730	-0.1033
	(0.1265)	(0.0203)	(0.3366)	(0.0910)	(0.2897)	(0.1014)
constant	-1.8942***		-3.5157***	-0.6356***		-0.8575***
	(0.1951)		(0.4378)	(0.1042)		(0.1309)
Observations	9,795		9,795	14,595		14,595
B. Female Children						
illness (within effect)	0.9547***	0.1482***	1.7328***	-0.1009***	-0.3141***	-0.0849***
	(0.1180)	(0.0179)	(0.2484)	(0.0268)	(0.0832)	(0.0250)
drought (within effect)	0.0477	0.0074	-0.0504	-0.0759***	-0.2364***	-0.0531*
	(0.1426)	(0.0222)	(0.3160)	(0.0290)	(0.0900)	(0.0281)
illness (b/n effect)	0.8526***	0.1324***	1.7382***	-0.0363	-0.1132	0.0054
	(0.1314)	(0.0210)	(0.2211)	(0.0746)	(0.2321)	(0.0869)
drought (b/n effect)	0.6713***	0.1042***	1.1657***	0.0674	0.2100	0.0047
	(0.2071)	(0.0326)	(0.3439)	(0.0939)	(0.2921)	(0.1066)
constant	-1.7203***		-3.2988***	-0.6152***		-0.7866***
	(0.2803)		(0.5141)	(0.1236)		(0.1556)
Observations	4,706		4,706	6,801		6,801
C. Male Children						
illness (within effect)	0.7621***	0.1235***	1.5601***	-0.0373	-0.1213	-0.0374*
	(0.1033)	(0.0172)	(0.2425)	(0.0229)	(0.0746)	(0.0208)
drought (within effect)	0.0300	0.0049	0.0837	-0.0324	-0.1053	-0.0409
	(0.1498)	(0.0243)	(0.3150)	(0.0274)	(0.0888)	(0.0258)
illness (b/n effect)	0.4166***	0.0675***	1.0071***	0.0177	0.0575	0.0381
	(0.1458)	(0.0234)	(0.2695)	(0.0693)	(0.2252)	(0.0923)
drought (b/n effect)	0.6818***	0.1105***	1.0111**	-0.1574	-0.5115	-0.2077
	(0.2350)	(0.0387)	(0.4146)	(0.1127)	(0.3645)	(0.1301)
constant	-2.0299***		-3.6084***	-0.6790***		-0.9416***
	(0.2833)		(0.5721)	(0.1205)		(0.1497)
Observations	5,089		5,089	7,794		7,794
Wald chi-square	76.66***			107.70***		

Robust standard errors in parentheses: Clustered at community level. $***p < 0.01, **p < 0.05, *p < 0.1$

All estimations include control variables listed in Appendix Table A2.3. AME stands for average marginal effect.

We used a Stata command written by Schunck and Perales (2017) for the meglm regressions.

Table 2.6: Recursive bivariate estimates on the impact of child illness on schooling outcomes

	(1)		(2)	
variables	Child illness Probit (AME)	Absenteeism Probit (AME)	Child illness Probit (AME)	Grade comp. Linear
A. All Children				
child illness		-0.0563		-1.7595***
		(0.1008)		(0.6078)
imp. toilet use	-0.0600***		-0.0711***	
	(0.0128)		(0.0144)	
drought (within effect)	0.0477***	0.0321	0.0456***	-0.2838***
	(0.0158)	(0.0236)	(0.0158)	(0.0889)
drought (b/n effect)	0.1201***	0.1436***	0.1133***	-0.0710
	(0.0221)	(0.0393)	(0.0221)	(0.3341)
constant				-1.2888***
				(0.3656)
Observations	14,532		14,579	
B. Female Children				
child illness		-0.0607		-2.0926***
		(0.1829)		(0.6685)
imp. toilet use	-0.0493**		-0.0718***	
	(0.0196)		(0.0200)	
drought (within effect)	0.0478**	0.0338	0.0417**	-0.3776***
	(0.0196)	(0.0282)	(0.0187)	(0.1130)
drought (b/n effect)	0.0880***	0.1393***	0.0876***	0.2472
	(0.0299)	(0.0473)	(0.0301)	(0.3455)
constant				-1.2265***
				(0.4397)
Observations	6,777		6,794	
C. Male Children				
child illness		-0.1326		-0.8788
		(0.0962)		(1.2229)
imp. toilet use	-0.0667***		-0.0698***	
	(0.0149)		(0.0174)	
drought (within effect)	0.0482***	0.0373	0.0477**	-0.2312**
	(0.0185)	(0.0278)	(0.0190)	(0.1152)
drought (b/n effect)	0.1447***	0.1683***	0.1353***	-0.4434
	(0.0211)	(0.0419)	(0.0222)	(0.4205)
constant				-1.4473***
				(0.4101)
Observations	7,755		7,785	
Wald chi-square	53.92***		79.18***	

Robust standard errors in parentheses: Clustered at community level. $***p < 0.01, **p < 0.05, *p < 0.1$

All estimations include control variables listed in Appendix Table A2.3. AME stands for average marginal effect.

We used a Stata command written by Roodman (2011) for the estimation.

attainment as a male child due to illness. Moreover, the adverse (direct) effect of drought on the highest formal school years completed is robust only for female children.

As described in section 4.5, we also used a recursive bivariate analysis with exclusion restriction to test the robustness of our findings presented in Table 2.5 and improve causal inference on the effect of child health on schooling outcomes. For identification, we exploit the exogenous variation in reported child illness related to access to an improved toilet facility, which is found to be a significant correlate to health status of a given child. The health equations in Table 2.6 show that reported child illness significantly decreases if the proportion of children in the community with access to improved toilet increases. Our estimation results presented in Table 2.6 provide robust evidence to suggest that drought causes illness, which, in turn, poses a detrimental impact on child education. On average, the probability of reported illness of a child increases by around 5 percentage points for a unit standard deviation increase in the magnitude of drought regardless of gender. In turn, child illness significantly decreases the highest completed formal schooling by around two years after accounting for observed and unobserved confounders. The adverse effect of child illness on the highest grade completed is statistically significant only for female children.

Our results imply that gender bias in the intra-household resource allocation to health care may explain the disproportionately large schooling effects of child illness on female children. We show in section 2.5.3 that there is no significant variation in the impact of drought shock on reported child illness based on sex of the child (Table 2.3). Therefore, female children are not more susceptible to drought-induced illness. Rather, households tend to divert health care spending away from them (Table 2.4). Consequently, female children are worse-off than male children in receiving medical treatment during illness when households experience income shocks. This ultimately results in significant variations between male and female children with respect to the effect of illness on schooling outcomes. In this respect, illness may linger on female children and negatively affects their education plausibly by affecting active engagement in schooling activities. Thus, households' gender-based coping response to drought-induced income shock results in variations in the effect that illness has on schooling outcomes of female and male children.

Pathways for the direct effect – Education expenditure and use of child labour: The direct within-child effects of drought, after accounting for its indirect (mediated) effect through child illness, on schooling outcomes are also shown in Tables 2.5 and Table 2.6. The within-child variation estimates reveal that drought on average resulted in a significant decline in the expected count of the highest grade completed. This effect is robust under alternative panel models only for female children. The expected number of count of a given female child's highest grade completed decreases on average by 0.3 as a result of an increase in the magnitude of drought by one standard deviation. Therefore, for a female child, drought bears a robust direct negative impact on her human capital development besides its mediated effect through ill health. After controlling for the negative and statistically significant effect of illness, the presence of a robust effect of drought on the education of female children implies that the income effect persists.

Table 2.7: The impact of drought shock on child labour use

variables	(1) Agri. work (*ln*) Linear	(2) Agri. work(*ln*) meglm-Linear	(3) Non-agri. work(*ln*) Linear	(4) Non-agri. work(*ln*) meglm-Linear	(5) Paid work(*ln*) Linear	(6) Paid work(*ln*) meglm-Linear
A. All Children						
drought (within effect)	-0.1697	-0.2463	0.3632*	0.4002*	-0.0106	0.0046
	(0.3042)	(0.3097)	(0.2075)	(0.2066)	(0.0354)	(0.0363)
drought (b/n effect)	-0.9195	-0.6669	-0.5498**	-0.4832**	0.1232***	0.0796*
	(0.5725)	(0.5107)	(0.2248)	(0.1911)	(0.0467)	(0.0414)
constant	-1.5899**	-1.8514***	-6.5233***	-6.4250***	-7.1049***	-7.0834***
	(0.6442)	(0.6087)	(0.3197)	(0.3049)	(0.0635)	(0.0619)
R-squared	0.1161		0.1123		0.0156	
Observations	14,403	14,403	14,389	14,389	14,392	14,392
B. Female Children						
drought (within effect)	-0.0448	-0.1060	0.5162**	0.5281**	-0.0288	-0.0249
	(0.3793)	(0.3773)	(0.2591)	(0.2498)	(0.0316)	(0.0333)
drought (b/n effect)	-1.3165**	-0.9597*	-0.4133	-0.2821	0.0219	0.0039
	(0.6376)	(0.5752)	(0.3354)	(0.2903)	(0.0408)	(0.0361)
constant	-1.3029*	-1.5288**	-6.5090***	-6.4330***	-7.0952***	-7.0780***
	(0.7830)	(0.4929)	(0.4274)	(0.4606)	(0.0672)	(0.0751)
R-squared	0.0658		0.1305		0.0155	
Observations	6,701	6,701	6,712	6,712	6,712	6,712
C. Male Children						
drought (within effect)	-0.2572	-0.3383	0.2477	0.3051	0.0078	0.0279
	(0.3327)	(0.3455)	(0.2019)	(0.2089)	(0.0538)	(0.0547)
drought (b/n effect)	-0.5960	-0.4041	-0.6686***	-0.6438***	0.2000***	0.1448**
	(0.6173)	(0.5522)	(0.2289)	(0.2018)	(0.0723)	(0.0654)
constant	-0.0759	-0.4492	-6.8004***	-6.7212***	-7.0852***	-7.0667***
	(0.7182)	(0.6682)	(0.3454)	(0.3416)	(0.0850)	(0.0889)
R-squared	0.1083		0.0982		0.0205	
Observations	7,702	7,702	7,677	7,677	7,680	7,680
Wald chi-square	481.09***		74.93***		53.36**	

Robust standard errors in parentheses: Clustered at community level. $***p < 0.01, **p < 0.05, *p < 0.1$

Björkman-Nyqvist (2013) and Randell and Gray (2016) suggest that households' measures to increase income or reduce expenditures during drought seasons may adversely affect children's schooling. They argue that households respond to income shocks by forcing children to drop out of school to engage in farm or non-farm activities and due to the reduced ability for households to pay for school fees and supplies. We explore these two mechanisms – education expenditure (school fees and supplies) and use of child labour – as plausible pathways for the direct effect of drought conditioning on gender. Unlike the gender bias in health care that we observe in 2.5.3, we do not find evidence that suggests gender-based variations in the intrahousehold resource allocation to education expenditure in the presence of drought. Appendix Table A2.8 shows that drought has a negative but not statistically significant effect on annual school expenditure. On the other hand, Table 2.7 shows that households' decision to use child labour in response to drought significantly vary based on gender. Drought increases the weekly hours of female child labour on non-agricultural activities on average by more than 50 percent (Panel B columns 3 and 4). Björkman-Nyqvist (2013) also found similar findings in Uganda where female children handle the majority of non-agricultural activities during periods of negative rainfall shocks. Committing a female child on non-farm activities may compete for her time that is needed for attending classes and studying to ensure progression to higher grades.

2.5.4 Further Robustness Check

We tested the robustness of our results for using a different school outcome variable. We used a child's ability to read and write in any language as a measure his/her literacy. Appendix Table A2.9 shows that drought has statistical significant adverse direct and mediated effect (through illness) on literacy of female children. These findings match the results presented in Table 2.5. Moreover, our analyses in the above sections are based on bounded drought shock variable that measures the magnitude of negative deviations from historical average precipitation and evapotranspiration. The absence of deviation from historical averages or positive deviations – more precipitation and low temperature – are bounded to be zero (see section 2.3.2). We probed the robustness of our findings by changing how the drought variable is defined. Following Mehr and Vaheddoost (2020), we created a categorical variable showing different levels of drought intensity. Appendix Table A2.10 shows that drought of higher magnitude has an adverse (direct and mediated) effect on a female child's highest grade completed. Thus, it is appropriate to take drought of an increasing intensity as a major risk factor to human capital development, in particular for female children.

2.6 Conclusion

While households in SSA are disproportionately affected by climate change and variability, children are the most vulnerable household members to the worst consequences of climate shocks. Our study examines the gendered impacts of climate shocks on health and schooling outcomes of children and contributes to the evidence base on the climate shocks-human capital nexus in the context of SSA. We also examine the possible short-run link between health and education to provide valuable insights into the contemporaneous direct and indirect (mediated) impacts of drought on child schooling outcomes – school absenteeism and highest grade completed. To this end, we merge child-level longitudinal data from the Ethiopia Rural Socioeconomic Survey (ERSS) with climate data. To improve causal identification, we take into account the presence of child- and household-level fixed effects that may either enhance or blunt the impact of climate shocks on a given child's human capital.

Using within-child variation estimators, we find that drought affects health status, school attendance, and the highest grade completed of children. While drought significantly increases reported child illness of both sexes, the impact appears to be more notable among female children. The impact of drought on education is also disproportionately concentrated on female children. The detrimental effect of drought on a female child's completed years of formal schooling is channelled, albeit not entirely, through illness. Our empirical assessment on the impact pathways show that households respond to drought shocks by altering the intra-household resource allocation to health care in a manner that diverts medication spending away from female children. Consequently, the negative effect of child illness on the highest grade completed is statistically significant and robust across alternative identification strategies only for female children. Besides the mediated effect through illness, drought has a direct and robust negative impact on a female child's number of formal school years completed, through increasing demand for female child labour for non-agricultural activities. This is consistent with our finding that the adverse effect of drought on school attendance grows stronger with age for a female child, while boys and younger girls are not affected.

In rural areas of SSA, households' income is highly constrained during drought seasons. Consequently, climate shocks impair human capital development of children that has long-term implications on their lifetime income generating capacity. The gender bias in the intrahousehold resource allocation and labour supply decisions introduces significant variations on the consequences of drought-induced income shocks on human development of children. Households' lack of coping capacity to maintain their spending on a female child's health care presumably limits her chance to recover and proceed with her schooling activities. Moreover, due to low expected return from agricultural practices in the presence of drought, households may look for options to supplement their income. In this respect, non-agricultural activities can be considered as a livelihood diversification strategy and may render the possibility to raise households' income and smooth food consumption. However, a female child bears the burden of handling the tasks associated with the households' non-agricultural activities, which ultimately compete with her schooling time. Therefore, household coping responses to climate shocks based on parents' perceived values of child labour and returns to education have long-term implications on the gender inequality in human development that may lead to feminized poverty.

Our study has a number of caveats. Despite we use within-child variation estimators and an exclusion restriction to account for the endogeneity of child health in the schooling equations, in the absence of experimental data, we cannot be completely sure that we exogenously varied health status to identify its causal mediation effect on child education. Furthermore, the available data also limit us to rely only on self-reported child health and schooling outcome variables, which may introduce measurement errors due to recall bias. Fortunately, existing research that investigates the reliability and construct validity of self-reports on health status and education shows consistency of responses comparing with objective measures (Sticca et al., 2017; Vaillant and Wolff, 2012) regardless of gender of respondents (Kuhn et al., 2006). Therefore, we argue that self-reported health status and schooling are salient child characteristics that are less likely to introduce recall bias in our estimations. In spite of this, future studies using different data sets that allow natural experiments and objective measures of child human capital (i.e. laboratory tests and screens, school attendance sheets, test scores) would verify the validity of our identification strategy and findings.

Based on our findings, we propose policies that either enhance households' income or minimize the costs of human capital investments in the face of climate change. On the income side, risk management policies and practices such as weather index insurance, social assistance, and climate-smart practices may ensure stable household income to allow investments on child health and education in the aftermath of drought. As such, easing households' liquidity constraints may eliminate adverse coping responses that lead to gender inequalities in human development. Understanding the contemporaneous links between child health and education in the presence of climate shocks is essential to setting policy priorities in health and education sectors. For instance, allowing free health care at public health facilities or school health programmes would pay "double dividend" by improving both health and schooling outcomes of children in the face of severe and frequent drought shocks. Since female children bear the brunt of the welfare effects of climate shocks, the issue of gender should be at the heart of conditionality in targeting beneficiaries of a policy or programme intervention that intends to spur human development in SSA in general and in Ethiopia in particular. For instance, conditional cash transfers to households based on female children's health visits and school attendance may eliminate the negative consequences of gender bias in intrahousehold resource allocation for health care services, and simultaneously may enable female children to attend school by reducing the opportunity cost of giving up a female child's labour. Future rigorous (comparative) evaluation studies may shed light on the effectiveness of such policy options.

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Appendix A2

Appendix Table A2.1: Mean differences in exposure to drought based on attrition

	Between survey waves 1 and 2			Between survey waves 2 and 3		
	Mean magnitude of drought		Mean	Mean magnitude of drought		Mean
Variables	Re-interv. HHs	Attrited HHs	diff.	Re-interv. HHs	Attrited HHs	diff.
Drought in 2011	0.3074	0.3322	-0.0248			
			(0.0314)			
Drought in 2012	0.0925	0.0802	0.0123			
			(0.0229)			
Drought in 2013	0.2127	0.2135	-0.0008	0.213	0.1706	0.0424
			(0.0272)			(0.0309)
Drought in 2014				0.0778	0.0632	0.0146
						(0.0176)
Drought in 2015				0.278	0.2617	0.0163
						(0.0278)
Observations	3,740	177		3,639	136	

Notes: Standard errors in parentheses. Out of the original 3,969 households that were surveyed in the first wave, a total of 330 households were not re-interviewed in the third survey wave. Between survey waves 1 and 2, 193 households were not re-interviewed.

Appendix Table A2.2: Mean differences in child human capital based on attrition

Variables	Children in re-interv. HHs		Children in attrited HHs		Mean diff.
	Number	Mean	Number	Mean	
Age	5667	11.7318	233	11.9914	-0.2596
					(0.2222)
Sex (% male)	5666	0.5224	233	0.4979	0.0246
					(0.0334)
Illness (%)	5611	0.1196	231	0.1515	-0.0319
					(0.0219)
Absenteeism (%)	3623	0.1336	135	0.1259	0.0077
					(0.0298)
Grade attainment	5533	2.3965	231	2.4416	-0.0450
					(0.1726)

Notes: Standard errors in parentheses. The number of children in the re-interviewed and attrited households is not the same for all variables that we considered for the mean difference test due to missing values in the variable of interest.

Appendix Table A2.3: Description and statistics of variables from the Ethiopian LSMS-ISA pooled panel data

Variables	Obs.	Description and coding	Mean	Std.Dev.	Min	Max
Variables of interest						
absenteeism	9,948	binary; =1 if the child was absent from school for more than a week in the past month, 0 otherwise.	0.101	0.302	0	1
highest grade completed	14,855	a count variable indicating the highest grade completed.	3.191	2.868	0	18
illness	14,953	binary; =1 if the child faced illness during the last 2 months, 0 otherwise.	0.096	0.295	0	1
medical treatment	1,437	binary; =1 if the ill child gets medical treatment, 0 otherwise.	0.683	0.465	0	1
inability to pay for treatment	413	binary; =1 if “lack of money” or “it is expensive” is a reason for not taking an ill child to medical treatment, 0 otherwise.	0.414	0.493	0	1
annual education expenditure (*ln*)	9.831	*ln* of child-level total annual education expenditure.	4.333	1.66	-6.908	9.045
agri. work hrs. per week (*ln*)	14,649	*ln* of the total hours in the last seven days that the child spend on household agricultural activities.	-2.278	4.888	-6.908	4.585
non-agri. work hrs. per week (*ln*)	14,636	*ln* of the total hours in the last seven days that the child spend to help any non-agricultural activities.	-6.167	2.567	-6.908	4.585
paid work hrs. per week (*ln*)	14,639	*ln* of the total hours in the last seven days that the child spend in any work for a wage, salary, or any payment.	-6.855	0.732	-6.908	4.564
annual food consp. exp. (*ln*)	7,172	*ln* of real annu. consumption exp. per ad. equ.	8.148	0.774	5.988	12.286
less meals per day	7,284	binary; =1 if the number of meals per day for the HH is twice or less, 0 for more than twice.	0.208	0.406	0	1
drought shock	16,987	a censored variable indicating magnitude of drought shock.	0.257	0.356	0	1.9
Control variables						
age of the child	16,916	continuous variable for the age of the child.	13.69	3.744	7	25
sex of the child	16,998	binary; =1 male child, 0 otherwise.	0.522	0.5	0	1
age of the HH head	16,890	Continuous; age of the household (HH) head.	48.45	12.26	15	98
sex of the HH head	16,993	binary; =1 male HH head, 0 otherwise.	0.799	0.401	0	1
attend school	16,901	binary; =1 if the HH head attended formal education, 0 otherwise.	0.35	0.477	0	1

Appendix Table A2.3: Continued

Variables	Obs.	Description and coding	Mean	Std.Dev.	Min	Max
family size	17,001	continuous variable indicating family size.	7.206	2.323	1	18
non-farm income sources	16,988	binary; =1 if the HH engage in activities that generate non-farm income, 0 otherwise.	0.324	0.468	0	1
private transfer	17,001	binary; =1 if the HH receive private transfers, 0 otherwise.	0.148	0.355	0	1
social assistance	16,951	binary; =I if the HH receive social transfers, 0 otherwise.	0.184	0.387	0	1
credit	16,913	binary; =1 if anyone in the HH borrow over the past 12 months, 0 otherwise.	0.27	0.444	0	1
total land	17,001	continuous variable indicating total land holdings in ha.	1.625	3.355	0	87.37
productive assets	17,001	continuous variable for productive assets index	0.495	1.058	-1.183	14.13
road distance	16,987	continuous variable for HH distance in (kms) to nearest road.	15.5	19.35	0	242
admin. center dist.	16,987	continuous variable for HH distance in (kms) to capital of zone.	167.7	126.8	1	773.1
district town	16,987	binary; =1 if the community is in a woreda (district) town, 0 otherwise.	0.119	0.323	0	1
region dummy1 (base group)	17,001	binary; =1 if Tigray region, 0 otherwise.	0.1006	0.3008	0	1
region dummy2	17,001	binary; =1 if Afar region, 0 otherwise.	0.0325	0.177	0	1
region dummy3	17,001	binary; =1 if Amhara region, 0 otherwise.	0.201	0.401	0	1
region dummy4	17,001	binary; =1 if Oromia region, 0 otherwise.	0.225	0.418	0	1
region dummy5	17,001	binary; =1 if Somali, 0 otherwise.	0.0586	0.235	0	1
region dummy6	17,001	binary; =1 if Benshangul Gumuz, 0 otherwise.	0.0309	0.173	0	1
region dummy7	17,001	binary; =1 if SNNP, 0 otherwise.	0.263	0.44	0	1
region dummy8	17,001	binary; =1 if Gambela, 0 otherwise.	0.0281	0.165	0	1
region dummy9	17,001	binary; =1 if Harari, 0 otherwise.	0.0289	0.168	0	1
region dummy10	17,001	binary; =1 if Diredawa, 0 otherwise.	0.0311	0.173	0	1
Survey year dummy1 (base year)	17,001	binary; =1 if the survey year is 2011, 0 otherwise.				
Survey year dummy2	17,001	binary; =1 if the survey year is 2013, 0 otherwise.				
Survey year dummy3	17,001	binary; =1 if the survey year is 2015, 0 otherwise.				

Appendix Table A2.4: Impact of drought on households' food consumption

variables	(1) Real food exp. per ad.eq. (*ln*) Linear	(2) Real food exp. per ad.eq. (*ln*) meglm-Linear	(3) Less meal-Probit Coeff.	(3) Less meal-Probit AME	(4) Less meal meglm-Logit
drought (within effect)	0.0456	0.0493	0.0453	0.0122	0.0930
	(0.0480)	(0.0488)	(0.1106)	(0.0297)	(0.2370)
drought (b/n effect)	-0.1560*	-0.1462*	0.2914	0.0782	0.6018
	(0.0866)	(0.0839)	(0.1797)	(0.0483)	(0.3880)
constant	8.7382***	8.7418***	-1.3184***		-2.7858***
	(0.1001)	(0.0995)	(0.2110)		(0.4687)
R-squared	0.1145				
Observations	7023	7023	7139	7139	7139

Robust standard errors in parentheses: Clustered at community level.

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

The dependent variable in column 1 and 2 is annual food consumption expenditure of the household after adjusting for inflation and households' composition (measured by adult equivalent), which are readily available in the ERSS panel data. The dependent variable in columns 3 and 4 is binary taking the value of 1 if the average number of meals in the household is twice or less, and 0 for three times or more.

All estimations include control variables listed in Appendix Table A2.3.

AME stands for average marginal effects.

We used a stata command written by Schunck and Perales (2017) for the meglm regressions.

Appendix Table A2.5: Impact of drought on children's long-term health outcome indicator

	(1)		(2)
variables	Probit (Stunting)		Stunting
	Coeff.	AME	meglm-Logit
A. All Children			
drought (within effect)	0.2407*	0.0910*	0.5689*
	(0.1322)	(0.0499)	(0.2924)
drought (between effect)	-0.1443	-0.0545	-0.1763
	(0.1782)	(0.0673)	(0.3228)
Constant	0.5402**		1.4131**
	(0.2631)		(0.5743)
Observations	2,700	2,700	2,700
B. Female Children			
drought (within effect)	0.2759	0.1028	0.6465*
	(0.1788)	(0.0664)	(0.3916)
drought (between effect)	-0.2188	-0.0815	-0.2683
	(0.2483)	(0.0923)	(0.4670)
Constant	1.0582***		2.2341***
	(0.3588)		(0.7727)
Observations	1,339	1,339	1,339
C. Male Children			
drought (within effect)	0.2246	0.0840	0.5938*
	(0.1567)	(0.0586)	(0.3407)
drought (between effect)	-0.0479	-0.0179	-0.1345
	(0.2263)	(0.0846)	(0.4105)
Constant	0.1734		0.6774
	(0.3223)		(0.7076)
Observations	1,361	1,361	1,361
Wald chi-square	47.15		

Robust standard errors in parentheses: Clustered at community level.

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

The dependent variable in column 1 and 2 is a binary variable taking the value of 1 if height-for-age z score (HAZ) of a child is less than -2 ($HAZ < -2$), and 0 otherwise.

All estimations include control variables listed in Appendix Table A2.3.

AME stands for average marginal effects.

We used a stata command written by Schunck and Perales (2017) for the meglm regressions.

Appendix Table A2.6: Seemingly unrelated model estimates child health and schooling outcomes

variables	(1) Health (illness) Probit-AME	(1) Absenteeism Probit-AME	(2) Health (illness) Probit-AME	(2) Grade Comp. Linear
A. All Children				
drought (within effect)	0.0384***	0.0156	0.0367**	-0.3286***
	(0.0145)	(0.0216)	(0.0145)	(0.0816)
drought (b/n effect)	0.1181***	0.1301***	0.1152***	-0.309
	(0.0217)	(-0.0323)	(0.0219)	(0.3167)
constant				-1.2896***
				(0.3637)
rho (ρ)	0.3930***		-0.0337*	
	(0.0304)		(0.0175)	
Observations	14580	14580	14580	14580
B. Female Children				
drought (within effect)	0.0441**	0.0191	0.0413**	-0.4311***
	(0.0187)	(0.0231)	(0.0187)	(0.1069)
drought (b/n effect)	0.0874***	0.1289***	0.0853***	0.0297
	(0.0293)	(0.0329)	(0.0295)	(0.3340)
constant				-1.2439***
				(0.4356)
rho (ρ)	0.4649***		-0.0595**	
	(0.0375)		(0.0243)	
Observations	6794	6794	6794	6794
C. Male Children				
drought (within effect)	0.0341**	0.0124	0.0333*	-0.2393**
	(0.0173)	(0.0255)	(0.0174)	(0.0967)
drought (b/n effect)	0.1395***	0.1329***	0.1360***	-0.5904
	(0.0216)	(0.0383)	(0.0218)	(0.3638)
constant				-1.3934***
				(0.4121)
rho (ρ)	0.3232***		-0.008	
	(0.0396)		(0.0232)	
Observations	7786	7786	7786	7786
Wald chi-square	70.18***		86.37***	

Robust standard errors in parentheses: Clustered at community level.

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

All estimations include control variables listed in Appendix Table A2.3.

AME stands for average marginal effects.

We used a Stata command written by Roodman (2011) for the estimation.

Appendix Table A2.7: Falsification test: test for the validity of the exclusion restriction

	(1) Absenteeism-Probit		(2) Absenteeism	(3) Grade comp.-Poisson		(4) Grade comp.
variables	Coeff.	AME	meglm-Logit	Coeff.	AME	meglm-Poisson
A. All Children						
imp. toilet (within effect)	-0.0058	-0.0008	0.0896	-0.0071	-0.0229	0.0188
	(0.1828)	(0.0262)	(0.3687)	(0.0340)	(0.1092)	(0.0304)
drought (within effect)	0.1155	0.0166	0.1432	-0.0591***	-0.1899***	-0.0581***
	(0.1368)	(0.0197)	(0.3025)	(0.0218)	(0.0698)	(0.0217)
constant	-2.0321***		-3.7929***	-0.6458***		-0.8213***
	(0.2639)		(0.4762)	(0.1073)		(0.1274)
Observations	8854		8854	13154		13154
B. Female Children						
imp. toilet (within effect)	-0.0618	-0.0084	-0.1215	0.0098	0.0307	0.0628
	(0.2211)	(0.0299)	(0.4644)	(0.0471)	(0.1483)	(0.0407)
drought (within effect)	0.1897	0.0257	0.1389	-0.0990***	-0.3119***	-0.0693**
	(0.1530)	(0.0210)	(0.3472)	(0.0333)	(0.1047)	(0.0306)
constant	-1.6880***		-3.3095***	-0.6905***		-0.7544***
	(0.3256)		(0.5730)	(0.1275)		(0.1500)
Observations	4238		4238	6098		6098
C. Male Children						
imp. toilet (within effect)	0.088	0.013	0.3228	-0.0188	-0.0616	-0.0109
	(0.2073)	(0.0307)	(0.4399)	(0.0410)	(0.1340)	(0.0368)
drought (within effect)	0.0337	0.005	0.0862	-0.0222	-0.0726	-0.0469*
	(0.1595)	(0.0236)	(0.3605)	(0.0305)	(0.0994)	(0.0261)
constant	-2.2484***		-4.0151***	-0.6436***		-0.8976***
	(0.3191)		(0.6216)	(0.1241)		(0.1496)
Observations	4616		4616	7056		7056
Wald chi-square	77.41***			116.25***		

Robust standard errors in parentheses: Clustered at community level.

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

All estimations include control variables listed in Appendix Table A2.3.

AME stands for average marginal effects.

We used a Stata command written by Schunck and Perales (2017) for meglm estimation.

Appendix Table A2.8: Impact of drought on total annual education expenditure

variables	(1) Total edu.exp. (*ln*) Linear	(2) Total edu.exp. (*ln*) meglm-Linear
A. All Children		
drought (within effect)	-0.1338	-0.1541
	(0.0916)	(0.0945)
drought (b/n effect)	0.1028	0.0688
	(0.1548)	(0.1221)
constant	2.5750***	3.0014***
	(0.2082)	(0.2612)
R-squared	0.1072	
Observations	9,684	9,684
B. Female Children		
drought (within effect)	-0.1048	-0.1884
	(0.1113)	(0.1189)
drought (b/n effect)	0.1059	0.1560
	(0.1758)	(0.1335)
constant	2.4320***	2.8218***
	(0.2535)	(0.3646)
R-squared	0.1071	
Observations	4,639	4,639
C. Male Children		
drought (within effect)	-0.1685	-0.1212
	(0.1160)	(0.1202)
drought (b/n effect)	0.0927	-0.0339
	(0.1742)	(0.1502)
constant	2.7189***	3.1655***
	(0.2414)	(0.2454)
R-squared	0.1196	
Observations	5,045	5,045
Wald chi-square	44.28	0.1914

Robust standard errors in parentheses: Clustered at community level.

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

All estimations include control variables listed in Appendix Table A2.3.

AME stands for average marginal effects.

We used a Stata command written by Schunck and Perales (2017) for meglm estimation.

Appendix Table A2.9: The direct and indirect effects of drought on child literacy

	(1)		(2)	(3)		(4)
	Literacy (Probit)		Literacy	Literacy (Probit)		Literacy
variables	Coeff.	AME	meglm-Logit	Coeff.	AME	meglm-Logit
A. All children						
drought (within effect)	-0.0822	-0.0247	-0.2540	-0.0785	-0.0236	-0.2495
	(0.0702)	(0.0211)	(0.1982)	(0.0537)	(0.0161)	(0.1978)
drought (between effect)	-0.0904	-0.0271	-0.3390	-0.0686	-0.0206	-0.2958
	(0.1731)	(0.0519)	(0.4170)	(0.1120)	(0.0336)	(0.4190)
illness (within effect)				-0.0929**	-0.0279**	-0.2373*
				(0.0424)	(0.0127)	(0.1311)
illness (between effect)				-0.1672*	-0.0502*	-0.3381
				(0.0889)	(0.0266)	(0.2581)
Constant	-0.7109***		-1.8999***	-0.7063***		-1.8852***
	(0.2014)		(0.5503)	(0.1526)		(0.5510)
Observations	14,628	14,628	14,628	14,628	14,628	14,628
B. Female children						
drought (within effect)	-0.1884**	-0.0572**	-0.4760**	-0.1835**	-0.0556**	-0.4693**
	(0.0805)	(0.0244)	(0.2319)	(0.0805)	(0.0244)	(0.2316)
drought (between effect)	0.2274	0.0690	0.0630	0.2451	0.0743	0.0876
	(0.1935)	(0.0589)	(0.4748)	(0.1927)	(0.0586)	(0.4756)
illness (within effect)				-0.1254**	-0.0380**	-0.3378**
				(0.0600)	(0.0182)	(0.1706)
illness (between effect)				-0.1778	-0.0539	-0.2719
				(0.1198)	(0.0363)	(0.3446)
Constant	-0.6491***		-1.5281**	-0.6412**		-1.5024**
	(0.2507)		(0.7296)	(0.2506)		(0.7303)
Observations	6,818	6,818	6,818	6,818	6,818	6,818
C. Male children						
drought (within effect)	0.0070	0.0020	-0.0858	0.0097	0.0028	-0.0828
	(0.0852)	(0.0250)	(0.2351)	(0.0851)	(0.0249)	(0.2353)
drought (between effect)	-0.3449*	-0.1011*	-0.6903	-0.3231*	-0.0946*	-0.6332
	(0.1918)	(0.0562)	(0.4827)	(0.1932)	(0.0566)	(0.4877)
illness (within effect)				-0.0586	-0.0172	-0.1415
				(0.0608)	(0.0178)	(0.1654)
illness (between effect)				-0.1388	-0.0407	-0.3579
				(0.1214)	(0.0355)	(0.3255)
Constant	-0.7399***		-2.1723***	-0.7402***		-2.1748***
	(0.2306)		(0.6194)	(0.2309)		(0.6206)
Observations	7,810	7,810	7,810	7,810	7,810	7,810
Wald chi-square	68.33***			68.43***		

Robust standard errors in parentheses: Clustered at community level.

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

All estimations include control variables listed in Appendix Table A2.3. AME stands for average marginal effects.

We used a Stata command written by Schunck and Perales (2017) for meglm estimation.

Appendix Table A2.10: The impact of categories of varying drought intensity on child health and grade completion

variables	(1) Illness AME (Probit)	(2) Illness meglm-Logit	(3) Grade comp. AME (Poisson)	(4) Grade comp. meglm-poisson	(5) Grade comp. AME (Poisson)	(6) Grade comp. meglm-poisson
A. All Children						
Near normal (within effect)	0.0117	0.1090	-0.0233	0.0065	-0.0212	0.0073
	(0.0106)	(0.1383)	(0.0518)	(0.0157)	(0.0515)	(0.0156)
moderate drought (within effect)	0.0307**	0.2535	-0.1232	-0.0598**	-0.1141	-0.0563*
	(0.0152)	(0.1834)	(0.1008)	(0.0304)	(0.1003)	(0.0302)
Severe and extreme drought (within effect)	0.0885**	1.0292*	-0.4713***	-0.1591***	-0.4280***	-0.1470***
	(0.0425)	(0.5383)	(0.1180)	(0.0452)	(0.1140)	(0.0449)
illness (within effect)					-0.2162***	-0.0588***
					(0.0602)	(0.0172)
Constant		-3.0323***		-0.8510***		-0.8502***
		(0.3442)		(0.1240)		(0.1237)
Observations	14,680	14,680	14,595	14,595	14,595	14,595
B. Female Children						
Near normal (within effect)	0.0078	0.0839	-0.0672	0.0024	-0.0640	0.0030
	(0.0150)	(0.1871)	(0.0674)	(0.0207)	(0.0668)	(0.0205)
moderate drought (within effect)	0.0408*	0.2649	-0.2275	-0.0594	-0.2117	-0.0543
	(0.0210)	(0.2507)	(0.1400)	(0.0422)	(0.1415)	(0.0425)
Severe and extreme drought (within effect)	0.0543	0.6016	-0.7483***	-0.2391***	-0.7102***	-0.2271***
	(0.0509)	(0.6075)	(0.1924)	(0.0522)	(0.1789)	(0.0490)
illness (within effect)					-0.3154***	-0.0845***
					(0.0836)	(0.0253)
Constant		-2.8108***		-0.7742***		-0.7727***
		(0.4443)		(0.1444)		(0.1443)
Observations	6,840	6,840	6,801	6,801	6,801	6,801

Appendix Table A2.10: Continued

variables	(1) Illness AME (Probit)	(2) Illness meglm-Logit	(3) Grade comp. AME (Poisson)	(4) Grade comp. meglm-poisson	(5) Grade comp. AME (Poisson)	(6) Grade comp. meglm-poisson
C. Male Children						
Near normal (within effect)	0.0150	0.1433	0.0329	0.0093	0.0342	0.0101
	(0.0118)	(0.1700)	(0.0695)	(0.0188)	(0.0693)	(0.0188)
moderate drought (within effect)	0.0255	0.2413	-0.0595	-0.0621	-0.0552	-0.0601
	(0.0188)	(0.2366)	(0.1312)	(0.0378)	(0.1303)	(0.0377)
Severe and extreme drought (within effect)	0.1127**	1.3033*	-0.3820*	-0.1117*	-0.3544	-0.1021
	(0.0530)	(0.6731)	(0.2210)	(0.0669)	(0.2170)	(0.0664)
illness (within effect)					-0.1213	-0.0371*
					(0.0743)	(0.0207)
Constant		-3.3872***		-0.9467***		-0.9466***
		(0.4091)		(0.1423)		(0.1421)
Observations	7,840	7,840	7,794	7,794	7,794	7,794
Wald chi-square	37.93		146.34***		147.19***	

Robust standard errors in parentheses: Clustered at community level.

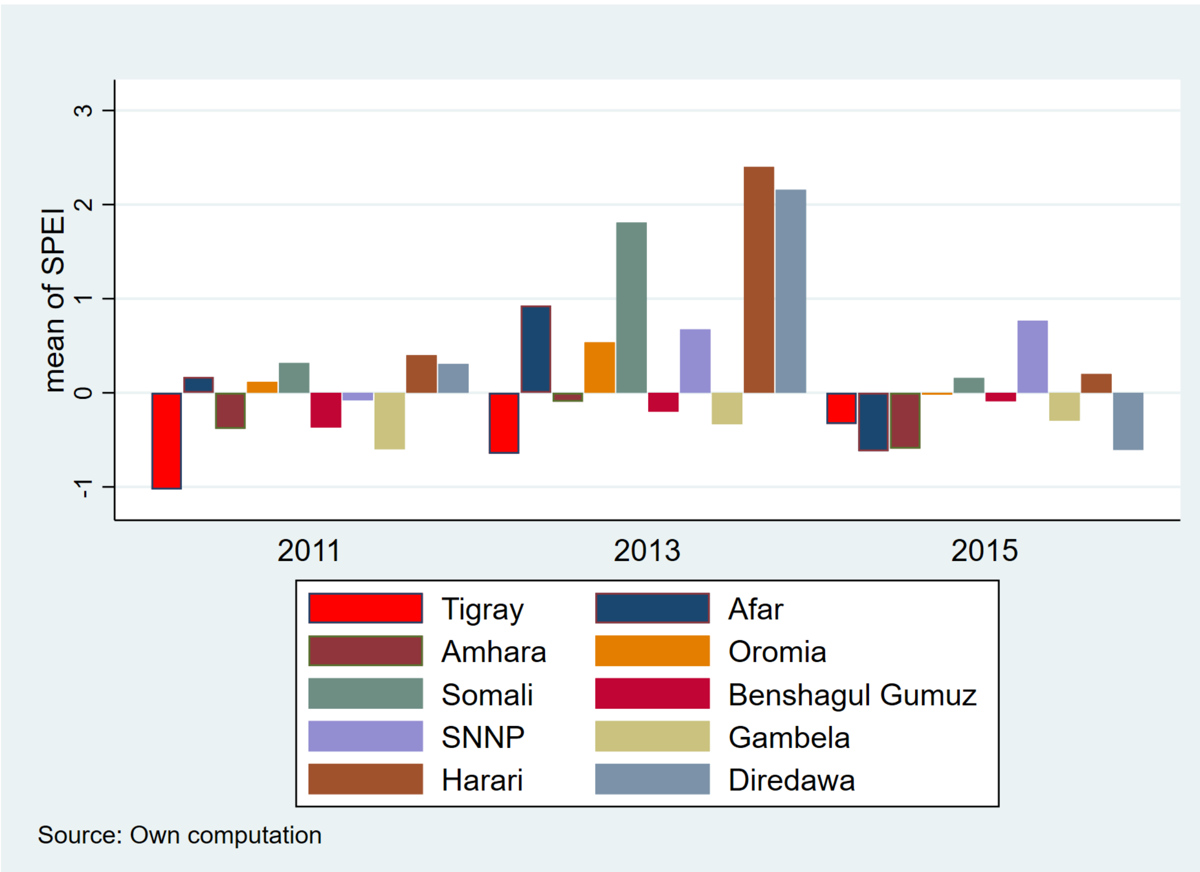
$***p < 0.01, **p < 0.05, *p < 0.1$

Categories of drought intensity: Base category (SPEI $>$ -0.5); Near normal (-0.5 $\geq$ SPEI $>$ -1); Moderate drought (-1 $\geq$ SPEI $\geq$ -1.42); and severe and extreme drought (SPEI $<$ -1.42).

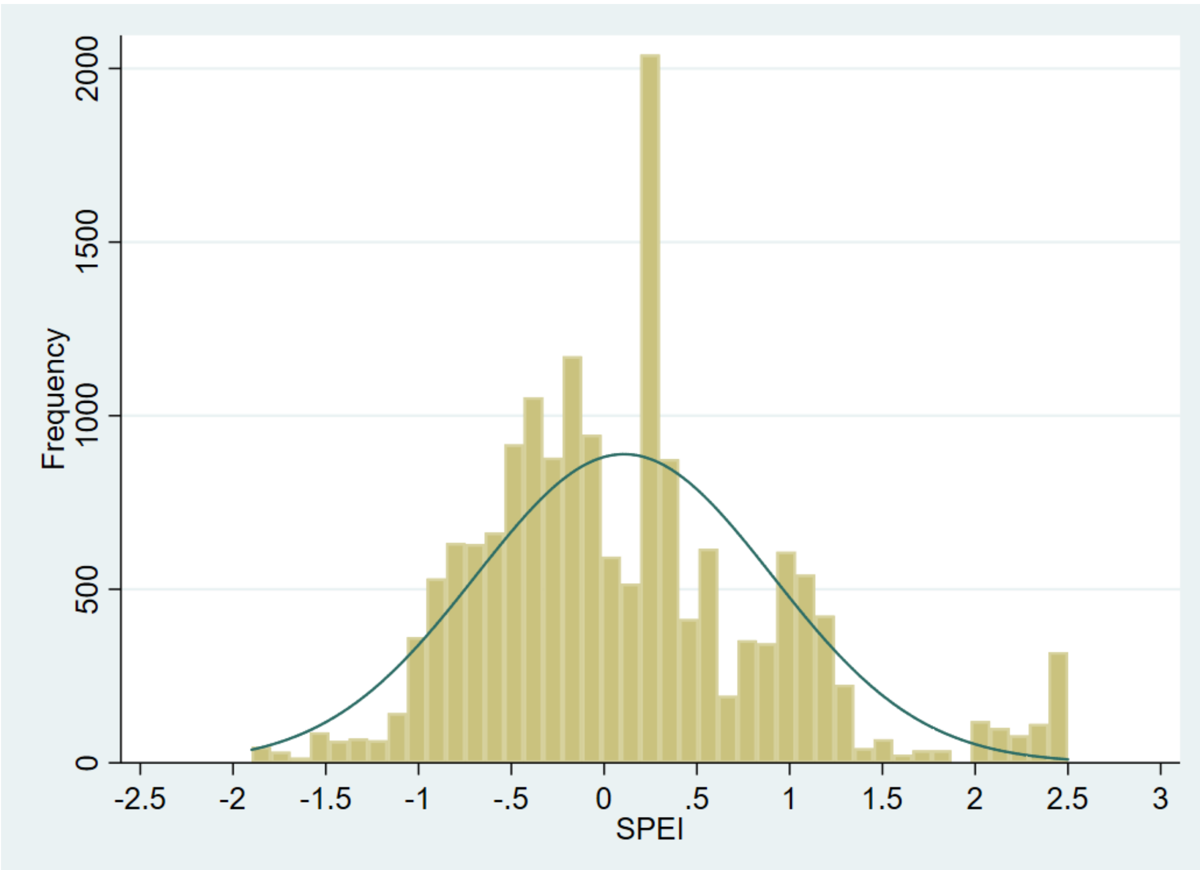
All estimations include control variables listed in Appendix Table A2.3.

AME stands for average marginal effects.

We used a Stata command written by Schunck and Perales (2017) for meglm estimation.



Appendix Figure A2.1: Distribution of SPEI values across regions by survey year



Appendix Figure A2.2: Distribution of SPEI values for the pooled data

CHAPTER 3

ELICITING RURAL HOUSEHOLDS' PREFERENCES FOR CLIMATE-SMART PRACTICES*

Abstract
This study examines rural households' preferences for the uptake of contractual climate-smart agroforestry that yields economic and ecosystem benefits. A discrete choice experiment was conducted with agricultural households in Ethiopia to elicit their willingness to participate in a payment for ecosystem services (PES) scheme that incentivises integrating faidherbia albida (a fertilizer tree) in their mono-cropping farming system. Attributes evaluated are "number of planted trees", "payment amount", "payment type", and "contract period". The presence of heterogeneity in the choice behaviour of households warrants the use of the generalized multinomial logit and latent class conditional logit models to allow for individual- and class-specific preferences, respectively. The results show that rural households derive higher utility from up-front payments. The households also strongly prefer food as the mode of payment than cash. Moreover, low numbers of mandatory planted trees and short-term contracts are found to be essential attributes that positively affect households' decisions to take-up a contractual arrangement to grow trees on their agricultural land. Our analysis also shows the presence of heterogeneity in preferences across segments of households in conjunction with differences in observable characteristics. These findings shed light on the considerations that must be accounted for when designing and implementing environmental policies such as PES schemes that promote large-scale adoption of climate-smart agricultural innovations, which mitigate climate risks.
Keywords: Climate-smart agroforestry; PES; Discrete choice experiment; Preference heterogeneity

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3.1 Introduction

Climate-smart agriculture (CSA) offers innovative possibilities for developing countries not only to buffer their agricultural production from the effects of climate shocks but also to orient agriculture as part of the solution to the climate change challenge (Campbell et al., 2014). The term CSA refers to a set of agricultural practices that can increase resilience to weather extremes through its "triple wins" of sustainably increasing agricultural productivity and incomes, adapting to climate change, and removing or reducing greenhouse gas emissions (FAO, 2010). Climate-smart agroforestry is one such practice which involves the integration of faidherbia albida (a fertilizer tree) into food crop systems (Akinnifesi et al., 2010; Garrity et al., 2010; Sida et al., 2018; Thierfelder et al., 2018). The practice comprises benefits associated with yield increments, and ecosystem services such as; mitigating climate risks by preventing global warming and desertification, protecting biodiversity, and reducing land degradation.

Climate-smart agroforestry improves soil structure and fertility, increases cereal production by 50-400 percent, reduces production costs by replacing around 75 percent of mineral fertilizers (Akinnifesi et al., 2010), and sequesters up to 4 tons of carbon per hectare per year (Mbow et al., 2014). Despite its economic and environmental benefits, the uptake of climate-smart agroforestry by rural households in sub-Saharan Africa (SSA) remains far less than optimal (Garrity et al., 2010; Glover et al., 2012). In the short run, tree planting in agricultural land involves making expenditures to maintain the trees without yield and financial returns as the production cycle is long. As a result, short-term income losses often inhibit agricultural households from investing in climate-smart practices which generate long-term economic and environmental returns (Neufeldt et al., 2011; Ndah et al., 2014).

The standard policy intervention in the face of positive environmental spillovers is to introduce incentives so that private individuals benefit from the use of environmentally responsible practices (Martin et al., 2014; Reed et al., 2015). Researchers and policymakers alike have advocated payments for ecosystem services (PES) as an incentive-based approach to internalizing the positive externalities of land use decisions. The conceptualization of PES is based on creating markets for trading ecosystem services, and correcting market failures that lead to their undersupply (Muradian et al., 2010). In a pure market-based PES, the primary concern is the improvement of environmental outcomes and not necessarily equity (Pagiola et al., 2005; Adhikari and Agrawal, 2013). Hence, such PES programs are more suitable for well-off farmers with well-defined property rights, low transaction costs, and better resource endowment (Sierra and Russman, 2006; Bremer et al., 2014; Lansing, 2017).

However, the poor and vulnerable rural households should be targeted as their inclusion will ensure sustainable land use and the Pareto-efficient provision of ecosystem services (Reed et al., 2015; Börner et al., 2017). If payments are set to reflect opportunity costs for ecosystem service providers, poor households, who have lower opportunity costs in absolute terms, would be the main beneficiaries of PES schemes (Muradian et al., 2010). Hence, the design and implementation of sustainable PES schemes that benefit the poor and vulnerable agricultural households should be guided by both efficiency and equity objectives (Leimona et al., 2015). To that end, the first step should involve understanding which attributes of a PES scheme influence the participation of poor farmers in the program. Eliciting households' stated preferences would uncover how they value the attributes of a proposed PES contract before launching the program. So far, a considerable amount of studies that elicit stated preferences have been conducted to understand the various natural, social and economic factors that determine participation in conservation- and restoration-oriented ecosystem service provision mainly via land retirement (i.e. the land should not be primarily used for farming activities).[1]

In the context of SSA, the exclusive planting of trees on private agricultural lands contradicts with the region's policy agenda which aim to increase agricultural production to feed the growing population. Climate-smart agroforestry could solve this policy dilemma by integrating the welfare and ecosystem concerns on rural households' agricultural land. However, few studies provide empirical evidence on the willingness of households to intercrop trees which generate multiple benefits for food security and the ecosystem. Notable examples are the work by Porras (2010) who found that the number of smallholder contracts has increased as a result of including agroforestry as a category in PES schemes in Costa Rica. Jack (2010) also assessed alternative market-based instruments for the efficient allocation of tree planting contracts on the private lands of smallholder farmers in Malawi. Cranford and Mourato (2014) used a discrete choice experiment (DCE) to examine farmers' preferences for a reduction in the cost of credit as a mode of payment for practising agroforestry in Ecuador.

This paper examines farmers' willingness to accept payments for planting fertilizer trees on their agricultural land in Ethiopia. Although the above-mentioned studies consider the eligibility of agroforestry under PES financing mechanisms, as any conventional PES program, the payment is ultimately attached to forest cover as a tradable ecosystem service. Put differently, farmers need to have the tradable commodity – grown up trees on their farm plots – before claiming incentives for their services to the environment. This study departs from the previous approach in that the hypothetical PES program rewards farmers for adopting climate-smart agroforestry from the initial year of planting the tree seedlings. Under this design, poor farmers can bear the short-term costs associated with their investment in the practice. Hence, this paper is a novel attempt at integrating efficiency and equity concerns in a PES scheme that accommodates agroforestry in the context of rainfed agriculture in SSA. A DCE is used to elicit farmers' preferences toward a PES program that would make annual payments as compensation for the direct and opportunity costs of investing in climate-smart agroforestry. In addition to the payment amount, the study also evaluates the relative importance of three additional attributes: required number of planted trees on the farm plots, payment type (cash or food), and contract period in years. The study also examines the socioeconomic factors that influence households' decision to accept the contractual tree planting

[1] See Whittington and Pagiola (2012) for a review on the application of stated preference methods for PES studies, and the stated preference-based PES studies listed under a meta-analysis by Hjerpe et al. (2015).

arrangement or remain with their current monocropping practice (the status quo).

We utilized a generalized multinomial logit (G-MNL) and latent class conditional logit (LCL) models to examine variations in the choice behaviour of individuals and classes of farmers, respectively. The G-MNL model accounts for both individual-specific scale and preference heterogeneity. All the G-MNL parameter estimates for the attributes considered in the PES program are statistically significant, an indication of the relevance of the chosen attributes. We find that rural households derive higher utility from up-front payments. Farmers are willing to receive a low amount if the mode of payment is food rather than cash. Moreover, low numbers of mandatory planted trees and short-term contract periods significantly motivated the take up of contractual agroforestry. We also find that households with a larger landholding and those who own a television or radio have stronger preferences for the PES contract than the status quo. The results from LCL model also show the presence of heterogeneity in preferences across segments of farmers in conjunction with differences in household characteristics. These findings provide policy-relevant information on the design considerations that must be taken into account for implementing PES contracts that promote adoption of climate-smart agroforestry among farmers in SSA and particularly in Ethiopia.

The remainder of the chapter is organized as follows. Section 3.2 describes the relevance of climate-smart agroforestry in the context of Ethiopia's development strategy. Section 3.3 provides a theoretical framework that links the concepts of climate-smart agroforestry and PES. Section 3.4 presents the source of data and data analysis techniques. Section 3.5 and section 3.6 present the results and discussion of the study, respectively. Section 3.7 concludes the paper.

3.2 Climate-Smart Agroforestry in the Context of Ethiopia

Ethiopia has given top priority to the agricultural sector as the basis for economic growth. However, the sector's sensitivity to the vagaries of weather and at the same time its contribution to climate change has caused a major concern. Out of the total (150 Mt CO2e) national greenhouse gas (GHG) emissions in 2010, 50 percent came from the production of agricultural output and around 20 percent are driven by deforestation for agricultural land (FDRE, 2011). Furthermore, the agriculture sector would add around 110 Mt CO2e in GHG emissions by 2030 if Ethiopia pursues a conventional development path (ibid). The conventional agricultural development path mainly involves the use of additional natural and physical resources for intensifying agricultural production, which would increase the carbon footprint as it has been observed in other parts of the world.

Shifting away from the conventional path, Ethiopia has devised a Climate Resilient Green Economy (CRGE) strategy that aims at overcoming the challenges of developing a green economy. The CRGE strategy is a blueprint to unleash Ethiopia's potential for a sustainable model of growth. Out of the four pillars that will support the strategy, two of them are related to agriculture: (i) adoption of land productivity- and efficiency-enhancing measures and (ii) increasing GHG sequestration in trees (i.e., planting trees for their economic and ecosystem services). Therefore, the strategy attempts to orient agriculture in a manner not only to significantly cut the contribution of the sector to the national GHG emissions but also to use agricultural soils as a sink for the emissions emanated from other sectors such as manufacturing and transportation.

To that end, agroforestry offers a possibility for abatement of GHG emissions by providing the greatest soil and above ground carbon sequestration in tropical areas (Feliciano et al., 2018). The Agricultural Extension Directorate of Ethiopia has given due emphasis for large-scale promotion and adoption of faidherbia albida in the country. As part of the activities outlined in the CRGE Strategy, in 2011, Ethiopia launched a national program to plant over 100 million *faidherbia albida* trees in the agricultural lands of smallholder farmers (Jirata et al., 2016). The agroforestry practice using *faidherbia albida* has been promoted to address issues of soil fertility, carbon sequestration, and resilience to climate variability. Integrating *faidherbia albida* trees in agricultural lands in Ethiopia has been documented to improve soil water retention, nitrogen and phosphorus use efficiencies, and green cover during the off-season (Sida et al., 2018). Despite Ethiopia's ambitious output-based target to reap the benefits from the large-scale adoption of climate-smart agroforestry, it has not been clear how to facilitate farmers' medium to long-term investment on the practice to realize the target.

3.3 Theoretical Framework

Poor households that are at the bare minimum in their current consumption cannot afford any decline in their current subsistence income, and hence find it hard to invest on agricultural innovations that do not provide immediate cash reward (Neufeldt et al., 2011). In the spirit of the reference-dependent utility model of Köszegi and Rabin (2006), the lack of uptake of agroforestry by smallholder farmers could be explained by the overemphasis farmers give to the loss in utility as a result of a decline in their reference (i.e. status quo) consumption level. Based on that, the short-term overall utility is given by $u(e|r) = m(e) + n(e|r)$, where $m(e)$ is the short-term consumption utility derived from planting *faidherbia albida* trees, and it is hardly different from zero. Whereas, $n(e|r)$ is the short-term utility loss due to climate-smart agroforestry, and it is determined by considering the foregone reference (status-quo) consumption level.

If a PES program compensates farmers for the direct and opportunity costs of investing in tree planting on their agricultural land, the disutility to farmers may be avoided and leave them indifferent between the status quo (i.e. mono-cropping) and adoption of climate-smart agroforestry. Therefore, it is an imperative theoretical and empirical inquiry to estimate farmers' willingness to accept compensations for short-term private losses emanating from conservation or restoration-oriented land use decisions such as adopting climate-smart agroforestry. To this end, we present a model of farmers' willingness to participate in a PES contract based on the agricultural household model that is shown in Singh et al. (1986); de Janvry et al. (1991); Taylor and Adelman (2003).

3.3.1 *Households' utility maximizing consumption function*

Due to market imperfections, quasi-universal circumstances in developing countries, farm households often act as a consuming (utility maximizing) and producing (profit maximizing) agents as a result of the non-separability between consumption and production decisions (Singh et al., 1986). Farm households strive to maximize utility from consumption of home-produced goods, marketed goods, and leisure. Agricultural goods are produced through farm technology represented by a production function.

$$Q = Q(L, X, \overline{R}) \tag{3.1}$$

where $L = \overline{T} - l_c$ is the labour used for the production of agricultural outputs given as the difference between the total time endowment ($\overline{T}$) and labour consumed for leisure (l_c). X is a vector of other variable inputs such as fertilizer. $\overline{R}$ is land endowment which is assumed to be fixed in the short-run. If the household is entirely subsistence, what is produced is entirely consumed ($C_f = Q$). But usually agricultural households in developing countries are semi-commercialized as they sell marketable surplus $M(M = Q - C_f)$: the households are net sellers if $M > 0$ and net buyers if $M < 0$. In this scenario, for agricultural households operating in a mono-cropping system, profits from agricultural production can be derived as:

$$\pi = p_y M - wL - p_x X \tag{3.2}$$

where π is profit in the mono-cropping system, p_y is the output price. The general price level has a positive (negative) effect on the profit of the net seller (net buyer) households. w is wage rate and p_x is a vector of prices of the other variable inputs. We assume that farmers face similar technology and private unit costs of production. The utility maximizing consumption level at the status quo – without agroforestry – is determined by:

$$C^* = C(C_f, \pi) \tag{3.3}$$

The introduction of agroforestry involves streams of added costs and reduced returns that affect the households' profit and ultimately their utility maximizing consumption. We only consider the period with no economic returns to households for investing in the practice. Accordingly, the profit in the case of agroforestry would be:

$$\pi_e = \pi - I \tag{3.4}$$

where π_e is profit in agroforestry, I is the present value of the total investment expenditure on agroforestry and it can be extended as:

$$I = (wl_e + \overline{E} + p_y Q_g)(1 + r)^{1-t} \tag{3.5}$$

where l_e is the labour utilized for agroforestry; $\overline{E}$ is expenditures on materials and equipment;

$Q_g = Q(\overline{F})$ is foregone food crop production as a result of land taken away by agroforestry where $\overline{F}$ is number of planted trees; r is time preference (subjective discount rate), which affects investments on profitable agricultural practices (Di Falco et al., 2019); t is number of years households are making expenditures on climate-smart agroforestry before getting positive economic gain attributable to the practice. Analogous to equation 3.3, in the short-run, the utility maximizing consumption in the climate-smart agroforestry system is:

$$C_e^* = C(C_f, \pi_e) \tag{3.6}$$

3.3.2 Modelling WTA and participation in PES contract

For the period without financial gains from climate-smart agroforestry, the measure of farmers' willingness to accept (WTA) compensation for renouncing their status quo utility maximizing consumption can be computed as:

$$WTA = [C^* = C(C_f, \pi)] - [C_e^* = C(C_f, \pi_e)] = I \tag{3.7}$$

The farmer is assumed to participate in the PES contract only if the contract payment offer is greater than or equal to WTA. Moreover, the design considerations for PES schemes go beyond the amount of payment, which is a function of output price, wage, and discount factor. Equation 3.5 shows that WTA (i.e, I) is also a function of the number of trees planted in the farm, and time (number of years that expenditures are made before realizing financial benefits). Since farm investment decisions are determined by consumption and production characteristics, WTA is also very likely to be affected by variables that affect production and consumption preferences. Therefore, farmers' willingness to participate in PES contracts (or accept compensation for foregoing the status quo) and their preferences for climate-smart agroforestry will be a function of household characteristics. For instance, access to available information influences an individual's knowledge, attitude, and perception, which are the main drivers of choice decision (Aryal et al., 2009). Moreover, farm income and wealth of the household are also the major determinants of the households' willingness to participate in PES programs (Katrina and Andreas, 2012; Li et al., 2017) and risk and time preferences (Tanaka et al., 2010). The following generalized model, which leads to our empirical model specification in section 4.3, presents farmers' willingness to participate in a PES program that rewards climate-smart agroforestry.

$$V_i = \alpha + \beta X_i + \gamma Z_i + \varepsilon_i \tag{3.8}$$

where V_i is the probability that the $i^t h$ household ($i = 1, 2, ..., n$) will participate in the PES contract (intercrop fertilizer trees) given a vector of PES attributes (X). Z is a vector of farm and farmer characteristics that are important determinants of preferences. α, β and γ are parameters to be estimated using the appropriate choice analysis technique.

3.4 Methodology

3.4.1 Description of the study area

The study was conducted in Hintalo Wajirat district which is one of the 34 rural districts of Tigray regional state in Northern Ethiopia (Appendix Figure A3.1). The study district is located South-East of Mekele, the capital city of Tigray region, and with GPS coordinates 13^0 09′ 60.00″ N and 39^0 39′ 59.99″ E. The district has a total area of 193,309 hectares of land and with an estimated total population of 170,243, out of which, 50.8 percent are females (CSA, 2013). Rainfed mixed crop-livestock farming is the primary source of livelihood in the district. Extreme environmental degradations in terms of soil erosion, loss of general biodiversity, and desertification have occurred throughout the district. In the past two decades, community-based conservation programs have played a significant role in mobilizing human and financial resources towards the construction of stone terraces, reforestation efforts, and enforcement of grazing restrictions (Birhane et al., 2017). The current policy priority of Tigray region in general and Hintalo-Wajirat district in particular is to showcase for large-scale adoption of *fadehrbia albida* which has been identified as a thriving agricultural innovation to enhance households' food security and reduce their vulnerability to the effects of climate change Noulekoun et al. (2017); Rinaudo (2010).

3.4.2 Source of data and method of data collection

Hintalo Wajirat district has a total of 22 tabias (kebeles)[2], which we could not cover them all in our survey due to financial and time constraints. We randomly selected seven tabias (Appendix Figure A3.1) and conducted a stated preference survey using a structured questionnaire to administer face-to-face interviews, from January to mid-February 2017, with 200 randomly selected rural households. Our structured questionnaire has sections to collect data on characteristics of the household head, demographic and socioeconomic variables of the household, and non-incentivised discrete choices on the adoption of contractual climate-smart agroforestry. We recruited enumerators from outside the study district and held a training session to build their understanding of the contents of the stated preference survey questionnaire. Stated preference methods uncover how individuals value different "alternatives" (whether goods, services, or courses of action) in a survey context (Louviere et al., 2010). In contrast to revealed preference methods using real-world data, stated preference studies are a standard tool for assessing people's preferences in hypothetical situations that do not currently exist, for instance before implementing a new PES program.

Contingent valuation method (CVM) and discrete choice experiment (DCE) are the two widely used approaches to elicit stated preferences from individuals. The CVM is an interview technique where people are asked to estimate the value they attach to certain alternatives directly. As long as the respondents are convinced that their responses will be used to help inform policy actions, the standard economic model suggests that economic agents will respond to the survey expecting to

[2]Tabia (kebele), which comprises villages, is the smallest administrative unit in Ethiopian federal government structure.

maximize their welfare (Carson, 2012). On the other hand, in DCE, respondents make choices between cleverly designed alternatives to estimate the weights that they place on each of the attributes that define the alternatives (Greiner et al., 2014). DCE has a sound theoretical foundation in random utility theory, which hypothesized that individuals are rational decision makers maximizing utility relative to their choices (McFadden, 1974).

The most common problems in stated preference methods are hypothetical and strategic biases. In the former case, what people actually do might not be the same as what they initially said they will do. Or, in the case of the latter, they might deliberately overstate or understate their true preferences to influence policy decisions that come out of the study. To minimize the hypothetical and strategic biases which are highly prevalent under the open-ended willingness to accept questions of CVM (Adamowicz et al., 1998), this study employed DCE. Moreover, "cheap talk" scripts have been common features of stated preference studies to minimize biased responses. "Cheap talk" scripts are attempts to minimize hypothetical and strategic biases by explicitly informing respondents that responses in hypothetical scenarios deviate from actual economic commitments (Cummings and Taylor, 1999; Carlsson et al., 2005; Tonsor and Shupp, 2011). Accordingly, while showing all sample farmers photos of climate-smart agroforestry that are depicted in Appendix Figure A3.2, a "cheap talk" script (presented under the figure) was read to enlighten them about the choices that they are requested to make and facilitate honest responses.

3.4.3 Design of the discrete choice experiment

The DCE design is generated following many sequential steps. The first step involves the decisions related to the selection of attributes, and attribute levels (Greiner et al., 2014). The attributes and their levels are determined based on the literature on agroforestry, and consultations with agricultural extension and natural resource management experts in the study area. Except for the attribute levels of the "payment amount", the other attributes along with their levels are identified based on the existing literature on PES and agroforestry. For optimal climate-smart agroforestry, the common practice is planting one hundred *faidherbia albida* tree seedlings per hectare with spacing at 10X10 meter (Fagg, 1995) and can be thinned down to 20-30 trees per hectare as the trees fully mature (Kang and Akinnifesi, 2000).

The "contract period" has levels that reflect the number of years farmers receive payments from the PES program. The levels are set based on the number of years farmers may wait before realizing positive net returns from their investments on climate-smart agroforestry. According to Baumer (1983), it will take at least 3-5 years after planting to see early signs of improvements in crop productivity that could be attributed to the presence of *faidherbia albida* trees in the farm plots. In most usual cases, it might take 10 years and above before farmers exploit the full economic benefits from climate-smart agroforestry (Akinnifesi et al., 2010). The classification of the "payment type" into cash or food is based on the argument that in the absence of complete product markets, under which poor smallholder farmers usually operate, the two modes of payments are distinct since one cannot readily be converted to the other (Currie and Gahvari, 2008).

Setting the levels for the "payment amount" requires the consideration of the direct and opportunity costs of climate-smart agroforestry. To this end, we conducted a private interview and field visits with 12 (6 crop production and 6 natural resource management) experts in the study area to identify the added financial costs and the reduced financial gains associated with planting 100 *faidherbia albida* trees per hectare on the lands of smallholder farmers. The direct costs include annual hired labour cost for planting and managing the trees in farm plots, costs for fencing the seedlings to avoid damage by humans or animals, and cost for the purchase of a pruning tool to remove damaged branches to protect the well-being of the trees.

We also considered the loss in farm income (the opportunity cost) due to planting trees on agricultural land. The experts estimated the area that 100 grown up *faidherbia albida* trees aging 10 years would take – which is the area of the trunk size. Based on each expert's response, we then calculated the income loss to farmers as a result of giving up the area that would have specifically been utilized for the production of wheat, which is predominantly grown in the study area. Therefore, the levels of the "payment amount" are non-conservative estimates, and determined considering four scenarios of the responses of the experts; (i) the minimum income loss estimate (ii) the median income loss estimates (iii) the mean income loss estimates, and (iv) the maximum income loss estimate. Table 3.1 presents the description and coding of the attributes, and the levels attached to each attribute. The attribute levels for the "payment amount" and "number of planted trees" are converted on the basis of *timad*[3].

Once the attributes and their levels have been determined, the second step is to combine them into alternatives which ultimately form the complete choice sets. The number of possible combinations of attribute levels, which is called the full factorial design, is very large (4x4x2x3=96). These can be combined into 4,560 pairs of alternatives [(96x95)/2 =4,560], which is too many to be practically feasible. Hence, the final fundamental step is combining the attribute levels into alternatives and choice sets in such a way so as to design a good DCE. A good DCE design is one that facilitates precision in the estimation of the attributes and that avoids problems prominent with revealed preference data, such as multicollinearity and limited variation in key variables (Johnson et al., 2013; Lancsar et al., 2017).

Efficient design and orthogonal design are the two competing experimental design generation procedures. A design is orthogonal when the attribute levels of the different alternatives are uncorrelated in the choice sets (Louviere et al., 2000). In recent years, efficient design is becoming more prevalent as an alternative procedure with new algorithms to facilitate the design. Efficiency is a measure of the level of precision in which the parameter estimates on the attributes are measured (Johnson et al., 2013). Efficient designs have been empirically shown to lead to smaller standard errors in model estimation at smaller sample sizes compared to orthogonal designs (Rose and Bliemer, 2013). This is a distinct advantage for this study given the small sample size. The most commonly used efficiency measure is D-efficiency which leads to the smallest generalized

[3] *Timad* is a local land area measuring unit which is more familiar to farmers than hectare. In the study area, one *timad* is equivalent to 0.25 ha.

variances of the parameter estimates (Louviere et al., 2008). For this study, during the design of a D-efficient DCE, the main considerations taken into account are; the number of blocks which comprise the total choice sets, the number of choice sets under each block, and the number of alternatives under each choice set.

Table 3.1: Description of the attributes and attribute levels

Attributes	**Description and coding of the attributes**	**Attribute levels**
Number of planted trees	The number of required faidherbia albida trees per timad that need to be planted in the farm plots.	5, 10, 20, 25
Payment amount	The annual payment in Ethiopian Birr (ETB). The amount of payment considers the additional financial costs and the reduced financial gains per timad associated with planting faidherbia albida trees in the farmers' plots.	125, 135, 155, 190
Payment type	A dummy variable for the payment type taking the value of 1 for food and 0 for cash. During the survey, the cash equivalent quantities of wheat in kg are presented in the choice tasks.	Cash, Food
Contract period	The total number of years farmers will be incentivised based on the number of existing faidherbia albida trees on their farm plots.	3, 5, 10

Note: 1 ETB is 0.044 U.S. Dollar (USD) based on the survey period average official exchange rate, which is obtained from OANDA currency converter (`http://www.oanda.com/currency/converter`).

A choice set with a large number of alternatives increases the cognitive burden on the respondents. A 3-alternative design is adopted in this study involving a choice between two hypothetical PES contracts and "neither of the two" (the status quo) option, which reflects the voluntary nature of farmers' participation in a PES scheme. This research applies the 'pick-one' format to better resemble real-life decision making. The number of choice sets that need to be included depends on the number of parameters to be estimated in the econometric model. In this study, there are 4 attributes and 8 household characteristics. Following the formula by Rose and Bliemer (2013), the required number of the choice sets for the DCE design are computed as; [12/(3-1)= 6]. Therefore, at least 6 choice sets should be presented to each respondent to generate the statistical minimum data points for the estimation of the parameters. This study went beyond the statistical minimum by setting 8 choice sets (see Table 2 for a sample choice set), after randomly dividing 16 choice sets into two blocks. After completing the DCE survey and excluding 6 sample households for incomplete responses in the choice experiment, the analysis is conducted based on a total of 4656 valid unlabelled discrete choices that are nested within 194 respondent farmers.

Table 3.2: Sample DCE choice set

Attributes	**Option 1**	**Option 2**	**Option 3**
Number of planted trees	10	25	Neither of the two
Payment amount (monetary value)	125	155	(the status quo)
Payment type	Wheat[†]	Birr	
Duration of the contract	5 years	3 years	
Which option would you choose?			

Note: [†] In option 1, the D-efficient design results in the payment amount of 125 ETB with a payment type in food (wheat) along with the other two attribute levels. The price for wheat during the survey period was 5 ETB per kg. Since the majority of the respondents are illiterate, we made the conversion of the monetary values into the actual amounts in the form of wheat (in option 1 for instance, we told farmers 125 ETB value of wheat means 25 kg).

3.4.4 Methods of data analysis

Empirical models specification

The analysis of DCE data relies on the framework provided by random utility theory where the choice problem is a problem of maximization of a utility function while the choices are observable indicators of utility. The conditional logit model (CLM), which is an extension of the multinomial logit model, developed by McFadden (1974) has been the workhorse econometric tool for analyzing discrete choice data. Accordingly, the utility that a farmer derives is given by:

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} \tag{3.9}$$

where U_{ijt} is the unobservable, but true utility for farmer i ($i = 1, 2, ..., N$) derived from choosing alternative j ($j = 1, 2, ..., J$) in a choice set t ($t = 1, 2, ..., T$). Relying on equation 3.8 in section 3.3.2, V_{ijt} is the observable or systematic component of the overall utility of farmer i choosing alternative j in the choice set t, and ε_{ijt} is the random component. The choice decision V_{ijt} is a function of the observable attributes of the alternatives in the choice sets and the observable characteristics of the respondent that do not vary across the choice sets. Hence, the specification for V_{ijt} is:

$$V_{ijt} = \alpha_j + X_{ijt}\beta + Z_i\delta_i \tag{3.10}$$

where X_{ijt} is a vector of observed attributes of alternative j and in choice set t, Z_i is the vector of socio-demographic characteristics of the farmer i, ε_{ijt} are disturbances assumed to be independently and identically distributed. α_j are alternative specific constants (ASCs) which represent a status quo intercept taking the value of 1 if farmers choose the status quo, and 0 otherwise. β is a vector of attribute-specific utility weights (homogenous across respondents), and δ_i is a vector of parameters to be estimated that are associated with household-specific characteristics (Z_i). Plugging equation 3.10 into equation 3.9 leads to the following specification.

$$U_{ijt} = \alpha_j + X_{ijt}\beta + Z_i\delta_i + \varepsilon_{ijt} \tag{3.11}$$

where the elements in the above specification are as described in equations 3.9 and 3.10. While CLM represents a natural starting point for estimating the parameters in equation 3.11, it imposes the unrealistic condition known as the independence of irrelevant alternatives (IIA), which states that the relative probabilities of two options being chosen are unaffected by the introduction or removal of other alternatives (Hausman and McFadden, 1984; Hensher and Greene, 2003). Hence, CLM cannot account for preference heterogeneity among respondents (or that their preferences depend only on observable characteristics). Moreover, CLM also restricts the percentage change in the probability for one alternative given a percentage change in the mth attribute of another alternative to remain the same (Hensher and Greene, 2003). If the IIA property is violated, CLM will result in biased parameter estimates.

In modelling individuals' choice, unobserved heterogeneity is pervasive and differential substitution patterns are likely to exist. The mixed logit (MIXL) model eliminates the limitations of the standard CLM by allowing the parameters in the model to vary across respondents. The basic structure of the specification under MIXL model remains identical to equation 3.11, but instead of β a vector of individual-specific coefficients β_i is estimated (Hensher and Greene, 2003; McFadden and Train, 2000; Train, 2009). Such that $\beta_i = \beta + \eta_i$, where η_i is a random vector distributed $MVN(0, \Sigma)$ and captures preference heterogeneity across respondents (Fiebig et al., 2010). However, a new strand of literature arise arguing that much of the preference heterogeneity may be better described as scale heterogeneity (SH) where β are fixed but the only variation between respondents is the scale of the idiosyncratic error term (Louviere et al., 2008). Building up from equation 3.11 after justifying scale heterogeneity as the source of variation in the attribute parameters, the estimation of β_i is $\beta_i = \sigma_i\beta$, where σ_i is a respondent-specific scale of the idiosyncratic error heterogeneity, distributed lognormal with standard deviation τ and mean $\overline{\sigma} + \delta Z_i$ (Fiebig et al., 2010).

To accommodate both preference and scale heterogeneity, Fiebig et al. (2010) developed a generalized multinomial logit (G-MNL) model that provides an appealing and tractable way to describe both types of heterogeneity with a single equation as $\beta_i = \sigma_i\beta + [\gamma + \sigma_i(1-\gamma)]\eta_i$, where γ is a scalar parameter, and η_i and σ_i are as described above. Estimating G-MNL without imposing a constraint on γ allows more flexibility in how preference and scale heterogeneities are combined (Keane and Wasi, 2013). However, this will increase the required number of data points for the estimation (Lancsar et al., 2017). Since the sample size of this study is relatively small, we constrained $\gamma = 0$ resulting in the type II generalized multinomial logit model (G-MNL-II) (Fiebig et al., 2010), which is also known as scaled MIXL model (Greene and Hensher, 2010). Based on this model, the utility to farmer i from choosing alternative j in choice set t is given by:

$$U_{ijt} = \alpha_j + X_{ijt}\sigma_i(\beta + \eta_i) + Z_i\delta_i + \varepsilon_{ijt} \tag{3.12}$$

The G-MNL model in equation 3.12 nests CL, MIXL, and SH models. When $\sigma_i = 1$ and $var(\eta_i) = 0$, the G-MNL specification revert back to CLM. When $\sigma_i = 1$, the estimation will be MIXL model. When $var(\eta_i) = 0$, the specification becomes the SH model. Moreover, in the estimation stage, the attributes (X_{ijt}) could be allowed to freely correlate with each other.

The latent class conditional logit (LCL) model was also employed to account for heterogeneity in preferences of groups of farmers. In LCL, farmers are sorted into a discrete number of latent classes (C) and distinctive taste parameters are estimated for each class, $\beta = (\beta_1, ..., \beta_C)$, which are heterogeneous across classes but homogeneous within a class (Boxall and Adamowicz, 2002). Following Greene and Hensher (2003), the LCL model is specified by taking a logit model as the central behavioural model where the choice probability that a farmer i ($i = 1, ..., N$) of class c chooses alternative j ($j = 1, ..., J$) from choice set t ($t = 1, ..., T$) as:

$$Pr(choice_{it} = J|class = c) = Pr_{it|c} = \frac{exp(\beta_c^{'} x_{itj})}{\sum_{K=1}^{J} exp(\beta_c^{'} x_{itk})}; \quad c = 1, ..., C \tag{3.13}$$

where $\beta_c^{'}$ is a vector of class-specific utility parameters associated with the vector of attributes x_{itj}. Given the class membership status is unknown, the unconditional likelihood of choices of farmer i needs to be specified. Following Pacifico and il Yoo (2013), the sample log-likelihood is then obtained by summing each respondent's log unconditional likelihood as:

$$lnL(\beta, \theta) = \sum_{i=1}^{N} ln \sum_{ci=1}^{C} \pi_{ic}(\theta) \prod_{t=1}^{T} Pr_{it|c} \tag{3.14}$$

where $\pi_{ic}(\theta)$ is the weight for class c. β and θ can be more conveniently estimated via a well-known Expectation-Maximization (EM) algorithm for likelihood maximization in the absence of information on each agent's class membership status (Pacifico and il Yoo, 2013). An issue to be noted is the choice of the number of classes. To decide the optimal number of classes, we used the value of C that minimizes the measures of variants of information criteria methods (Louviere et al., 2000).

Estimating marginal willingness to accept

The WTA measure for an attribute corresponds to a compensatory payment that farmers, on average, would be willing to accept to make a one-unit improvement in the attribute level (or to adopt a category of an attribute) in the case of negative values and to give up in the case of positive values. WTA measures on the attributes provide a convenient way for comparing the marginal utility weights that respondents assign to the attributes. Calculating WTA measures could follow estimation either in the preference space or in the WTA space. In the former, a distribution of coefficients in the utility function is specified and then a distribution of the WTA is later derived. We follow the standard approach that assumes the attribute coefficients are normally distributed and the payment coefficient is fixed to compute the WTA as the ratio of the coefficient for a given attribute (β_A) to the negative of the payment attribute coefficient (β_P), as;

$$WTA_A = \frac{\beta_A}{-\beta_P} \tag{3.15}$$

The main problem with fixing the distribution of the payment coefficient while estimating the WTA in the preference space is that all individuals are assumed to have the same marginal utility of income (Meijer and Rouwendal, 2006), and variation in scale would be erroneously translated into variation in WTA resulting in untenably large WTA measures (Train and Weeks, 2005). To solve the problem of artifact measures, Train and Weeks (2005) recommend computing reasonable WTA estimates directly in the WTA space as presented in equation 3.16. Accordingly, we applied maximum simulated likelihood after re-formulating the model in such a way that the distributional assumptions are made directly on the WTA measures.

$$U_{ijt} = \lambda_i(-P_{ijt} + \gamma_i x_{ijt}) + \varepsilon_{ijt} \tag{3.16}$$

where U_{ijt} is as described under equation (9), P_{ijt} is the payment attribute, x_{ijt} is non-payment attributes, $\lambda_i = \frac{\beta_{Pi}}{\sigma_i}$, $\gamma_i = \frac{c_i}{\lambda_i}$, and $c_i = \frac{\beta_{Ai}}{\sigma_i}$. ε_{ijt} is the disturbance term distributed with variance given by $\sigma_i^2(\frac{\pi^2}{6})$. σ is scale of the idiosyncratic error heterogeneity. β_A is a vector of parameter estimates of non-payment attributes to be estimated on WTA space.

3.5 Results

3.5.1 Descriptive statistics

This study hypothesizes that the household characteristics, particularly those (closely) related to farmers' perception on climate-smart agroforestry, income or wealth, and access to information can influence their preferences to participate in a PES program that promotes fertilizer tree planting (see section 3.3.2). Table 3.3 presents the household level variables that are included in the analyses. Namely, these variables are: gender, age, and educational status of the household head; family size; total land holding; access to agricultural extension services; membership to informal information sharing and self-help farmer groups (*iddir*); and ownership of television or radio. The means and standard deviations for the continuous variables and the proportion of households with responses equal to 1 for the binary variables are reported in the table. Given that the household characteristics do not differ between each choice set, they were entered into the regression models through interactions with the alternative specific constants (status quo intercepts). Including these effects in the analysis minimizes biases that would otherwise arise in the parameter estimates of the main effects (the attributes).

Table 3.3: Household level characteristics

Household characteristics	Coding	Percent	Mean	SD
Sex of the head	1 if Male; 0 otherwise	73		
Age of the head	Number of years		48.59	14.15
Family size	Number of household members		5.76	2.29
Landholding	Total land size in hectare		0.92	0.94
Education status	1 if read and write; 0 otherwise	37		
Extension contact	1 if Yes; 0 otherwise	77		
Iddir membership	1 if Yes; 0 otherwise	61		
Owns television or radio	1 if Yes; 0 otherwise	35		

Note: SD stands for standard deviation.

Out of our sample 200 rural households that faced 8 choice-sets each involving a choice between two alternative PES contract options and the status quo (see Table 3.2 for a sample choice set), we collected complete responses on 194 households. Around 11 percent of the respondents (22 households) consistently opt against PES program regardless of the varying attributes in the alternatives of the PES options and prefer the status quo (mono-cropping farming system) in all their choices. Such a choice behaviour could be best explained by a bias towards the status quo (Samuelson and Zeckhauser, 1988; Dean et al., 2017) that prevents farmers from adopting climate-smart agroforestry. The remaining 89 percent of the respondents supported the PES program depending on the contract attributes in the choice sets. This high level of preference towards the PES contract implies that the choice sets offer plausible and salient options to incentivise farmers to practice climate-smart agroforestry. Table 3.4 reports mean difference tests on household characteristics based on whether respondent farmers consistently opt against PES contract (i.e. choose only the status quo) for the entire choice sets.[4] The averages show that sample households who consistently choose the status quo are more likely to be female-headed, have smaller family size, and are less likely to own TV or radio.

3.5.2 G-MNL model results - Farmer-specific preference heterogeneities

Columns 1 and 2 in Table 3.5 present the parameter estimates for the choice analysis under G-MNL uncorrelated and G-MNL correlated models, respectively.[5] The parameter estimates from the uncorrelated G-MNL (column 1) are used as starting values for the final G-MNL correlated model. Post estimations following the correlated models offers insight on preference heterogeneity, which

[4]We thank the anonymous reviewers for pointing out that it would be informative to assess whether respondents who consistently opted out of the PES program have distinct household characteristics.

[5]The coefficients on the attributes, intercept and its interaction with household characteristics are estimated under the specification of equation 3.12 using Stata 15. The G-MNL model was estimated via simulated maximum likelihood using the user-written Stata commands developed by Gu et al. (2013).

Table 3.4: Mean differences in household characteristics based on choice behaviour

Household characteristics	Choice decision (in favor of) PES contract (at least once)	No-PES contract (always the status quo)	Mean difference
Sex of the head	0.75	0.55	0.20**
Age of the head	48.2	51.64	-3.44
Family size	5.94	4.37	1.57***
Landholding	0.95	0.72	0.23
Education status	0.38	0.32	0.06
Extension contact	0.78	0.68	0.1
Iddir membership	0.63	0.46	0.17
Owns television or radio	0.38	0.14	0.24**

is estimated as the deviations from the mean utility weights attached to the attributes. Since the observations in the choice experiment are not independent, all standard errors are cluster-robust at the household level. For brevity, only the results from the correlated G-MNL model are discussed. There are two main reasons for making this choice. First, in addition to the significant presence of preference heterogeneity (i.e., the statistically significant standard deviations around the mean utility weights on the attributes), the standard deviation of the respondent-specific scale of the idiosyncratic error heterogeneity (τ) is highly significant. These results signal the presence of preference and scale heterogeneities, and hence the G-MNL model is more appropriate than MIXL model (parameter estimates are shown in Appendix Table A3.1) as it accounts for both types of heterogeneity. Second, goodness-of-fit tests using log-likelihood (LL), Akaike information criteria (AIC) and Bayesian information criteria (BIC) show that the correlated G-MNL had the best fit for the data than the uncorrelated G-MNL.

Table 3.5 column 2 shows that the coefficients on all attributes are statistically significant, an indication of their relevance to the PES programme. As expected, the attribute “payment amount” has a positive coefficient, an indication that farmers derive higher utility from higher payment amounts. Farmers also demonstrate strong preferences for food as a mode of payment than cash. Intuitively, cash might be thought to dominate farmers’ choice since payments in cash give more flexibility and expand the array expenditure choices. However, one should closely scrutinize the contextual environment where farmers are making their choices. The failure of output markets could explain farmers’ preference towards payment in food rather than in cash. The study area is characterized by its vulnerability to climate shocks and the associated severe food shortage (Gebrehiwot and der Veen, 2013). In the absence of well-functioning markets that mobilize food items from surplus to deficit areas, cash transfers are vulnerable to price increases of food items thereby eroding the purchasing power of the transfers (Sabates-Wheeler and Devereux, 2010). Therefore, farmers would rationally choose the end good (food) rather than the means (cash). Similar preference to receive food over cash was also observed among the participants of a national safety net program (PSNP) in Ethiopia (Devereux et al., 2006; Wiseman et al., 2010) because cash transfers are not regularly adjusted to inflation rates (Baye et al., 2014).

The coefficients of "number of trees" and "contract period" are negative indicating that, on average, farmers strongly prefer low numbers of required planted trees and short-term contract periods. Loss aversion may prevent farmers from adopting innovations with unknown returns (Fafchamps, 2009). Since climate-smart agroforestry is not a common practice in the study area, loss-aversion is a plausible explanation for farmers' reluctance to fully commit their land and time to plant and maintain *faidherbia albida* trees. Further analysis shows that except for the correlation between payment in food and contract period, the non-diagonal terms in the covariance matrix of the attributes are positive and statistically significant (Table A3.2 in the Appendix). Preference towards planting more trees is positively and significantly associated with their preference for food payments. Similarly, there is a positive and significant correlation between the number of planted trees and contract period.

Turning to the interactions between household-level characteristics and the ASC (choosing the status quo over PES options), the results show that farmers with larger landholdings and those who own television or radio strongly prefer the PES contract over the status quo. The positive and significant effect of landholding on farmers' choice to enroll in a PES program is well documented in recent studies by Bremer et al. (2014) in Ecuador and Lansing (2017) in Costa Rica.[6] Landholding is a key determinant of the household's farm income generating capacity and a good proxy for the households' wealth especially in agrarian economies (Alesina and Rodrik, 1994). Consequently, farm income and wealth are highly correlated with risk-taking behaviour and patience of the households (Tanaka et al., 2010). Hence, farmers with larger landholdings are more willing to accept new practices with future gains.

There are two plausible explanations on the significant effect of ownership of television or radio on farmers' participation in the PES program. One is acquiring these durable assets can also signal the households' wealth, and hence the above discussion still holds. The other possible explanation is that as ownership of information media these channels may determine access to information that could positively shape farmers' knowledge and attitudes towards climate-smart agroforestry and therefore affect their willingness to accept the PES program. However, we are not aware of any national or local TV or radio program specifically designed to promote agroforestry. Hence, further research in this direction may reveal the practicality of our suggestive explanation. Other demographic and socio-economic variables are not statistically significant predictors. For the variables sex of the head and family size of the households, we observed statistically significant mean differences between households who consistently opt against the PES scheme and the remaining households (Table 3.4). After conditioning on other household characteristics, the variations cease to exist under our preferred model (Table 3.5 column 2).

[6]It should be noted that, especially in the context of landholding, farmers in Latin America and sub-Saharan Africa countries are quite distinct. Smallholder farming on less than 2 ha of land is the major livelihood activity of rural households in SSA in general and in Ethiopia in particular.

Table 3.5: Parameter estimates of the G-MNL model

	(1)		(2)	
	Uncorrelated G-MNL		Correlated G-MNL	
variables	Mean	SD	Mean	SD
Payment amount	0.0154**		0.0138***	
	(0.0074)		(0.0045)	
Number of trees	-0.0512**	0.1346***	-0.0408**	0.1846***
	(0.0215)	(0.0443)	(0.0171)	(0.0306)
Payment in food	3.5628*	6.9466**	1.8846***	5.7263***
	(1.8278)	(2.8443)	(0.4394)	(0.9500)
Contract period	-0.2263*	0.9517***	-0.1367**	0.5980***
	(0.1294)	(0.3568)	(0.0580)	(0.1122)
τ	-0.7263**		-0.5875***	
	(0.3092)		(0.1407)	
ASC	-0.7616		0.4801	
	(3.9328)		(5.5431)	
ASCXAge	0.0724		0.0440	
	(0.0593)		(0.0914)	
ASCXSex	-3.2760*		-2.8743	
	(1.7774)		(4.7459)	
ASCXEducation	1.8962		1.0666	
	(1.6168)		(2.6231)	
ASCXFamily size	-0.2509		-0.2987	
	(0.2111)		(0.5718)	
ASCXLandholding	-1.1483*		-1.3111**	
	(0.6815)		(0.6570)	
ASCXExtension contact	0.7441		0.6704	
	(1.1498)		(2.1211)	
ASCXTvoradio	-4.5662**		-4.1057*	
	(2.2929)		(2.2389)	
ASCXIddir member	-3.0362**		-2.8475	
	(1.2859)		(1.9464)	
Observations	4,656		4,656	
AIC	1702.64		1662.07	
BIC	1812.22		1790.99	
Log-likelihood	-834.3		-811.0	

Note: Robust standard errors in parenthesis.

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

The standard deviations (SD) on the attributes capture preference heterogeneity across farmers.

3.5.3 Willingness to accept measures

The WTA estimates – estimates of the marginal utility of receiving payment – under both the preference and WTA spaces are presented in Table 3.6. However, for the reasons presented in section 3.4.4, we only offer interpretations based on the WTA measures that are estimated in the WTA space.[7] Farmers are willing to receive around 59 ETB (2.60 USD) less in annual payment per *timad*, which is 0.25 hectare (ha) of land, if the mode of payment is food rather than cash. Farmers are willing to accept 1 ETB per *timad* (0.18 USD per ha) per year if they have to plant an additional *faidherbia albida* tree on their farm plot. Farmers are also willing to accept additional annual payment that worth around 2 ETB per *timad* (0.35 USD per ha) for an increase in the PES contract by a year.

Table 3.6: Willingness to accept measures in the preference and WTA space

Attributes	Preference space† – Correlated G-MNL (in ETB)	WTA space (in ETB)
Number of Trees	2.9494	0.9924*** (0.1735)
Payment in food	-136.3085	-58.8229*** (2.3842)
Contract period	9.884	1.8401*** (0.5493)

Note: Robust standard errors in parenthesis. *** $p<0.01$

† The ratio of the attribute coefficient to the negative of the coefficient for the "payment amount" attribute from Table 3.5 column 2. 1 ETB is 0.044 USD based on the survey period average official exchange rate.

3.5.4 Insights from the LCL model - Class-specific preference heterogeneities

The results from the LCL model offer insight into the variations in the preferences across different segments of agricultural households by allowing the attribute coefficients to vary across the (latent) classes. The selection of the optimal number of latent classes was based on consistent Akaike Information Criteria (CAIC) and BIC, which are more critical toward models with more parameters by using penalty functions that increase in the number of respondents. As shown in Table 3.7, CAIC and BIC are at their lowest for five classes – types of farmers with different preferences for PES contract attributes. The household characteristics (described in Table 3.3) are used for predicting class membership to separate respondents with different preferences for the attributes.

Table 3.8 reports the regression coefficients of the LCL model using 5 latent classes.[8] The heterogeneity of preferences is reflected in the different parameter estimates for the attributes across

[7] This study used a Stata code developed by Hole (2016)

[8] The estimation is based on the Stata code developed by Pacifico and il Yoo (2013)

Table 3.7: Selection criteria for an optimal number of latent classes

Classes	LLF	Number of parameters	CAIC	BIC
2	-1042.4	17	2191.88	2147.88
3	-830.67	30	1850.14	1820.14
4	-786.19	43	1843	1800
5	-743.28	56	1838.99	1782.99
6	-730.53	69	1895.3	1826.3

the segments. The mean (over respondents) highest posterior probability of class membership is about 0.95, which indicates that the model adequately differentiates the underlying heterogeneity in preferences for the observed choice behaviour. While class 3 has the highest average membership probability of 38%, class 5 has the lowest (12%). Given that there are 3 alternatives in a given choice set, the (un)conditional probability of actual choice examines the model's ability to make in-sample predictions of the actual choice outcomes (without) conditioning on being in a given class c. The LCL model describes the observed choice behaviour in each class with a significantly higher average predicted probability of actual choice after conditioning on respondents' membership probability. For instance, the class 5 average unconditional probability of choosing the actual alternative was 24%, whereas this likelihood increased to 80% conditional on membership probability.

Table 3.8: Class-specific attribute coefficients in LCL model

Attributes	Class 1	Class2	Class3	Class4	Class5
Payment amount	0.0354***	0.0103***	0.0198**	0.0228***	-0.0339***
	(0.0051)	(0.0026)	(0.0091)	(0.0030)	(0.0105)
Number of trees	-0.1252***	0.0204	0.0087	0.0157	0.0079
	(0.0262)	(0.0130)	(0.0254)	(0.0162)	(0.0620)
Payment in food	0.8887***	0.202	4.5637***	-1.9433***	1.1645
	(0.2871)	(0.1924)	(0.6538)	(0.2507)	(1.1598)
Contract period	-0.3160***	0.2146***	-0.1938	-0.0025	-0.0979
	(0.0695)	(0.0448)	(0.1385)	(0.0417)	(0.1891)
Class share	0.15	0.18	0.38	0.17	0.12
Unconditional prob.	0.5	0.47	0.6	0.37	0.24
Conditional prob.	0.65	0.6	0.96	0.72	0.8

Note: Robust standard errors in parenthesis.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Respondents in class 1 have statistically significant coefficients for all the attributes, indicating that farmers in this segment care about all of the PES program design features. Class 2 consists of a group of farmers that derive higher utility from a PES program with a higher payment amount and longer contract period. In this class, the respondents' utility weights attached to the number of planted trees and payment in food are not statistically different from zero. Respondents in class 3 exhibit strong preferences for a higher amount of payment in the form of food (wheat). Class 4 comprises farmers whose preferences are the exact opposite of those in class 3. Respondents in class 4 derive higher utility by receiving a high amount of payment in the form of cash.

Unlike the previous 4 classes, the payment amount coefficient for respondents in class 5 is negative and significant at 1% probability level. The coefficients for the remaining attributes in this class are not statistically different from zero. This indicates that farmers in class 5 are strongly against receiving payments from the PES program. Even though there is no theory-based explanation for this result, an incident that had occurred in the study area involving agricultural households and coordinators of a cash transfer pilot program may provide a behavioural explanation. In 2011, UNICEF Ethiopia launched a cash transfer pilot program in Hintalo Wajirat district also targeting our sample tabias. However, some households wrongly perceived that they were deliberately targeted based on their religion and were being offered money to change their faith. The implementation of the program was only realized after awareness meetings with the households to explain the real intention of the cash transfers. Based on personal communication with the cash transfer coordinator officer in the study area, the issue had sporadically arisen until the official completion of the pilot program in 2014. Despite explaining the purpose of the PES payments in the 'cheap talk' script of the DCE survey (stated under Figure A3.2 in the Appendix), our finding may also point to the presence of a segment of farmers that strongly oppose any payments with monetary value because of persistent misconceptions on the intentions of the payments.[9] Appendix Table A3.3 presents the WTA value of each attribute in each latent class. The WTA measures are computed in the same manner as measuring WTA in the preference space – the ratio of the attribute coefficient to the negative of the coefficient for "payment amount" attribute.

Further analyses on variations in household characteristics of farmers in the various classes are shown in Table 3.9. The household characteristics across the segments of farmers are compared using the 5th class as a base category, where the household characteristics are normalized to 0 for identification. Hence, we can compare the household characteristics of farmers in class 5 with farmers in the remaining classes who have demonstrated a strong common desire towards higher up-front payments. Accordingly, as measured by their membership to an informal self-help farmer groups (*iddir*), farmers in class 5 are worse-off in terms of their social capital than those in class 1. Farmers in class 5 have smaller landholdings but are more likely to be able to read and write than households in class 2. Class 5 also comprises farmers that are less likely to own TV or radio than those in class 3 and class 4. Moreover, farmers in class 5 have smaller family size than farmers in class 4.

[9] We do not have prior knowledge about the incident during the survey or data analysis. We learn about it while trying to provide a possible explanation for the observed result.

Table 3.9: Variations in household characteristics between classes of farmers

Household characteristics	Class 1	Class 2	Class 3	Class 4	Class 5
Age	0.0009	-0.0138	-0.0141	-0.0011	Fixed parameter
	(0.0232)	(0.0229)	(0.0181)	(0.0225)	
Sex	1.1969	1.2743	0.6186	-0.1737	Fixed parameter
	(0.9141)	(0.8227)	(0.6698)	(0.7935)	
Education	-0.3733	-1.6915**	-0.4958	0.3218	Fixed parameter
	(0.7488)	(0.8304)	(0.6206)	(0.7210)	
Family size	0.1343	-0.0105	0.2196	0.3303*	Fixed parameter
	(0.1779)	(0.1642)	(0.1415)	(0.1754)	
Total land	0.3764	0.8804*	0.0719	-0.994	Fixed parameter
	(0.4218)	(0.4550)	(0.4058)	(0.7442)	
Extension contact	-0.2132	18.4000	-0.4262	-0.5110	Fixed parameter
	(0.7989)	(311.567)	(0.6079)	(0.7292)	
Owns tv\radio	0.5791	1.1834	1.3811*	1.8657**	Fixed parameter
	(0.8796)	(0.8048)	(0.7156)	(0.7936)	
Iddir membership	1.9776***	0.8824	0.8516	-0.2513	Fixed parameter
	(0.7554)	(0.6531)	(0.5214)	(0.6290)	
Constant	-2.8091*	-18.9334	-0.101	-0.7946	Fixed parameter
	(1.6813)	(311.5671)	(1.1843)	(1.4221)	

3.6 Discussion

Climate-smart agroforestry renders economic benefits by sustainably increasing agricultural productivity and incomes, and ecosystem services by sequestering greenhouse gas emissions, and protecting land and biodiversity (Akinnifesi et al., 2010; Garrity et al., 2010). While conventional PES schemes reward climate-smart agroforestry in developing countries, the payments are made only after farmers provide the outputs (grown-up trees) that render ecosystem services. In the analogy of conditional cash transfers, for example, assuming that households are eligible for social assistance for their children schooling, the timing of the transfers in a conventional PES design may mean poor and vulnerable households would only receive the transfers after their children graduate from high school or college. On the contrary, the design of our hypothetical PES scheme resembles an equity-oriented conditional cash transfer in exchange for the initial farmers' decision to plant fertilizer trees (*faidherbia albida*) within their agricultural land. In this respect, our PES design takes into account the fact that farmers in SSA are highly financially constrained (Karlan et al., 2014) which makes them reluctant to invest in agricultural practices that do not result in immediate cash inflows (Neufeldt et al., 2011). Respondent farmers in our study exhibit a strong preference for the up-front PES payments in the form of food. They also prefer higher annual payments for a few years than small amounts that are made for many years.

Therefore, changing the timing of payment in a PES program may trigger a change in behaviour among rural households in SSA in favor of climate-smart agroforestry, which has economic and ecosystem benefits. If a PES program compensates farmers for the investment costs associated with adopting climate-smart agroforestry at the initial years, when cash outflows characterize the investment, farmers are willing to engage in an environmentally conscious land use (planting trees) and there is a high possibility for large-scale adoption of the innovation across the landscapes of SSA. The current adoption rate in semi-arid and sub-humid Ethiopia is 26 percent (Iiyama et al., 2017). Based on the design features of our study's PES scheme, almost 90 percent of sample respondents welcome the idea of adopting the innovation.

It is also important to take into account that attributes of PES schemes are not equally weighted by different segments of farmers that are classified based on variations in their choice decisions and household characteristics. We observe that there is a class of households that are firmly against receiving payments from a PES program. Moreover, farmers in different classes also assign different utility weights to the non-payment attributes. In general, our understanding of the household and community contexts that farmers are operating and making decisions is vital to develop outreach strategies for successful implementation of agri-environmental policies such as PES interventions. Income and wealth have been significant household characteristics that influence households participation in a PES scheme (Bremer et al., 2014; Lansing, 2017). Even in the context of smallholder farmers that are characterized to operate on average landholding of smaller than 2 ha (Lowder et al., 2016) variables such as landholding and ownership of durable assets that can proxy the households' income and wealth significantly affects their willingness to participate in a contractual agroforestry practice under a PES scheme.

3.7 Conclusion

A DCE survey, which is constructed using a D-efficient design procedure, was conducted on 200 rural households in Ethiopia to estimate the utility weights they assign on various design features of a hypothetical PES program that promotes the planting of fertilizer trees on their agricultural land. The use of the G-MNL and LCL models allow for individual- and class-specific preferences, respectively. The results from G-MNL model show that rural households derive higher utility from higher amounts of up-front payments. Moreover, households prefer a PES program that uses food (wheat) as payment, requires a low number of planted trees and has a shorter contract period. Households are willing to receive lower annual payments if the payments are in food rather than cash. Conversely, they demand extra annual payments for the planting of an additional fertilizer tree and extension of the PES contract by a year. The results from LCL model show the presence of heterogeneity in preferences across segments of farmers in conjunction with differences in household characteristics.

The study also finds that households' landholding and ownership of a television or radio – which can serve as proxies for income and wealth – positively influences their preference for the

PES program. Ownership of TV or radio may also proxy households' access to information media. Hence, the other suggestive explanation is that the mass media may serve as channels for raising community awareness on climate-smart agroforestry. Further research in this direction may reveal the practicality of our suggestive explanation. The lack of effect of agricultural extension services on households' choice behaviour is a red flag regarding the emphasis given to agroforestry in the regional extension package. There is, therefore, need to further investigate how fertilizer trees are promoted by the extension service and if methods of promotion are effective and need to be changed.

The study is a novel contribution to the PES literature as the design of the PES program features payments starting from the initial year, as opposed to conventional PES programs that pay after the ecosystem services are realized. The study's payment arrangement is suitable for poor and vulnerable rural households as it rewards an environmentally conscious land use (planting trees) that has delayed climate risk mitigating and ecosystem benefits. The results shed light on the design considerations that must be taken into account for integrating efficiency and equity objectives in PES programs that accommodate agroforestry in the context of rainfed farming systems in SSA. The study reveals the presence of individual- and class-specific heterogeneous preferences on the design features of the PES scheme. Hence, practitioners and policy makers should develop strategies to increase outreach beyond the average household to achieve successful implementation of environmental policies that promote large-scale uptake of climate-smart agricultural innovations.

Despite the study employs DCE design and a "cheap-talk" script to facilitate truth telling, it should be noted that responses to our hypothetical questions may deviate systematically from responses observed in real world interactions. We suggest future research to employ a "cheap talk" script after a pre-test on the comparative performance of alternative scripts to improve rigour. Furthermore, future field experiments based on the design features of our DCE study will show the practicality of our findings.

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Appendix A3

Appendix Table A3.1: Parameter estimates of the MIXL model

	(1)		(2)	
	Uncorrelated MIXL		Correlated MIXL	
variables	Mean	SD	Mean	SD
Payment amount	0.0093***		0.0094***	
	(0.0034)		(0.0030)	
Number of trees	-0.0378***	0.0992***	-0.0278*	0.1466***
	(0.0136)	(0.0143)	(0.0142)	(0.0228)
Payment in food	2.0757***	4.7647***	1.5569***	4.5633***
	(0.4015)	(0.6178)	(0.4228)	(0.5832)
Contract period	-0.1416***	0.6044***	-0.0986**	0.4712***
	(0.0453)	(0.0799)	(0.0497)	(0.0647)
ASC	-0.2541		0.4231	
	(2.1726)		(2.7845)	
ASCXAge	0.0415		0.0270	
	(0.0308)		(0.0394)	
ASCXSex	-2.0110**		-1.9021	
	(1.0088)		(1.9938)	
ASCXEducation	1.2148		0.8108	
	(0.8932)		(1.3499)	
ASCXFamily size	-0.1974		-0.2762	
	(0.1822)		(0.3130)	
ASCXLandholding	-0.7352		-0.7635	
	(0.4751)		(0.4828)	
ASCXExtension contact	0.4549		0.3852	
	(0.8664)		(1.0697)	
ASCXTvoradio	-2.9163***		-2.9163**	
	(0.9070)		(1.2075)	
ASCXIddir member	-2.0365***		-2.3367**	
	(0.7331)		(0.9244)	
Observations	4,656		4,656	
AIC	1704.95		1666.85	
BIC	1808.09		1789.32	
Log-likelihood	-836.5		-814.4	

Note: Robust standard errors in parenthesis.

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

The standard deviations (SD) on the attributes capture preference heterogeneity across farmers.

The MIXL model was estimated via simulated maximum likelihood using the user-written Stata commands developed by Hole (2007).

Appendix Table A3.2: Variance-covariance matrix of the coefficients in the correlated G-MNL model

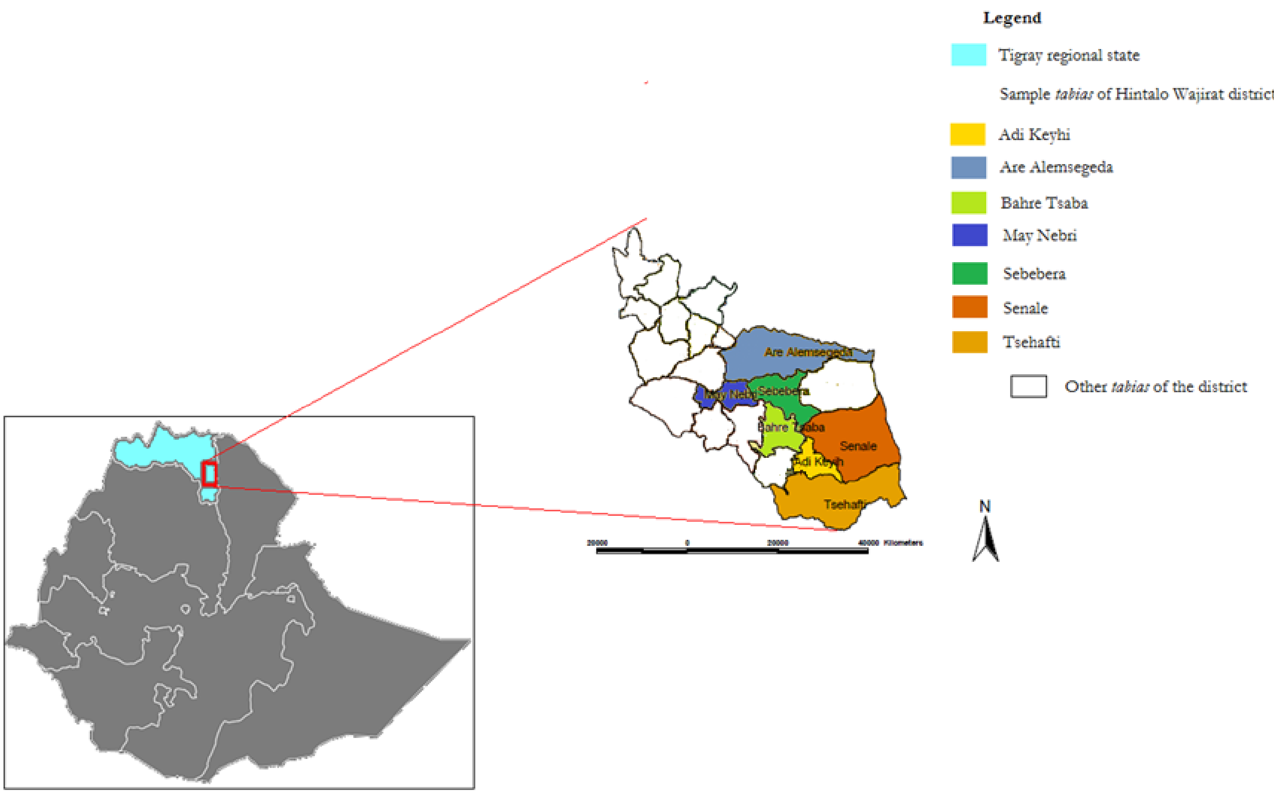
Coefficients	Number of trees	Payment in food	Contract period
Number of trees	0.0341***		
	-0.0113		
Payment in food	0.5899***	32.7907***	
	-0.1968	-10.8806	
Contract period	0.0883***	0.7869	0.3576***
	-0.0319	-0.6979	-0.1342

Note: Robust standard errors in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table A3.3: WTA measures of LCL

WTA measures	Class 1	Class 2	Class 3	Class 4	Class 5
Number of trees	3.54 (2.66,4.42)	-1.97 (-4.82,0.87)	-0.44 (-3.12,2.24)	-0.69 (-2.13,0.75)	0.23 (-3.28,3.74)
Payment in food	-25.12 (-39.39,-10.84)	-19.58 (-59.18,20.03)	-231.04 (-416.24,-45.85)	85.32 (61.01,109.63)	34.31 (-26.03,94.64)
Contract period	8.93 (6.62,11.24)	-20.8 (-34.68,-6.91)	9.81 (-0.61,20.24)	0.11 (-3.47,3.69)	-2.89 (-14.67,8.90)

Note: Lower and upper limits in the parenthesis.



Appendix Figure A3.1: Map of the study area

Appendix Figure A3.2: Photos of climate-smart agroforestry presented to all sample respondents

Note: To the left: *Faidherbia albida* trees on agricultural land before sowing annual crops (Photo: A. Agard). To the right: *Faidherbia albida* trees intercropped with annual crops (Photo: Hadgu)

The following "cheap talk" script was read to all sample farmers while presenting the photos.

Now you are kindly requested to make choices between three alternatives. Suppose you are facing production decisions involving two alternatives where you would be incentivised (in-cash or in-kind) for planting faidherbia albida trees on your agricultural land and a third alternative with an option to choose the status quo (an alternative that you can say "I do not want to plant trees in my farm plots"). There are no "correct" or "wrong" choices but you have to make priorities among the three alternatives and make only one choice in each choice set. Please be honest and reflect your choice as if it would be implemented right now for real, i.e. either you would plant the number of faidherbia albida tree seedlings within your agricultural land in exchange for annual payments (in-cash or in-kind) that will be made for a given number of years as specified in your choice or you would not plant the trees.

CHAPTER 4

IMPACT OF FORMAL CLIMATE RISK TRANSFER MECHANISMS ON RISK-AVERSION: EMPIRICAL EVIDENCE FROM RURAL ETHIOPIA*

Abstract

This study examines the effect of smallholder farmers' access to a formal climate risk transfer mechanism on their risk preferences. Survey and experimental data were collected from smallholder farmers that have access to weather index-based crop insurance (WICI) in Ethiopia. We use an endogenous switching (ESP) model to address self-selection and simultaneity biases. Results from the ESP model show that farmers who purchased WICI are less likely to be risk-averse compared with the counterfactual scenario of being non-purchaser farmers. Similarly, non-purchasers would have attained a significant reduction in their risk-aversion if they had taken up the insurance product. We also find that WICI has a positive and statistically significant effect on farmers' real-life risk-taking behaviour as exemplified by mineral fertilizer use. The implication of our findings is that formal climate risk transfer mechanisms can positively influence rural household farm investment decisions, by reducing their risk-aversion. Therefore, they can possibly contribute to poverty alleviation and economic development within agrarian economies that are exposed to recurrent and severe climate shocks.

Keywords: Weather index-based crop insurance, endogenous risk preferences, experimental risk elicitation, endogenous switching probit, sub-Saharan Africa, Ethiopia

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4.1 Introduction

Agricultural households in sub-Saharan Africa (SSA) are facing more frequent and severe climate risks than ever before (Masih et al., 2014; Shiferaw et al., 2014). The absence or inaccessibility of formal credit and insurance markets limits the ability of agricultural households to withstand the effects of climate shocks (Karlan et al., 2014), and has been a key determinant of longer-term poverty dynamics (Chantarat et al., 2007; Barnett et al., 2008). In the presence of uninsured weather shocks, any reduction in rural households' agricultural production can have detrimental impacts on food and income available for consumption (Hertel and Rosch, 2010). Hence, most households respond by altering their economic behaviour and decisions, which have repercussions on their production. In this respect, it is generally assumed that farmers in developing countries are risk-averse as an ex-ante response to minimize the climate shock-induced income variability that they frequently experience. Accordingly, the households will "self-insure" by engaging in low-risk low-return agricultural activities (Rosenzweig and Binswanger, 1993) which in the short-run may seem sub-optimal. However, in the long-term, risk aversion ultimately traps agricultural households in persistent poverty (Carter and Barrett, 2006; Yesuf and Bluffstone, 2009; Dercon and Christiaensen, 2011).

Risk-aversion is a significant determinant of households' decisions that lead to: low investments in higher-income farm enterprise combinations (Nyikal and Kosura, 2005), assigning a lower value to education attainment (Brown et al., 2012), and low adoption of agricultural technologies (Liu, 2013; Ward and Singh, 2015; Brick and Visser, 2015; Holden and Quiggin, 2017). At the aggregate level, households' low investments in physical and human capital may further aggravate the productivity lag and income inequality in rural areas of SSA (Odusola et al., 2017), where high inequality has constrained poverty reduction efforts (Fosu, 2015). Hence, risk-aversion is linked to development prospects of a country by influencing households' production, consumption, and labour supply decisions which in turn determine the accumulation of human, physical, and financial capital.

In light of this, there has been a growing interest in developing weather index-based crop insurance (WICI) schemes that provide a transparent risk transferring mechanism for smallholder farmers to help them better manage climate risks and exhibit risk-taking behaviour in their agricultural practices (Barnett et al., 2008). Few studies analyse the impact of WICI on households' decision to invest in high-risk high-return activities (Hill and Viceisza, 2012; Mobarak and Rosenzweig, 2012; Karlan et al., 2014). These studies examine how improving access to formal insurance markets affects farmers' willingness to take risky investment decisions using field experiments in developing countries. However, such an approach simultaneously captures risk preferences, beliefs about the background risk (i.e. uninsurable idiosyncratic risks associated with the investment), and opportunities to engage in a given behaviour (e.g. available investment options) (Schildberg-hörisch, 2018). Furthermore, these studies implicitly take risk preferences as stable over time and exogenous in the WICI impact pathways. Hence, the fixity of farmers' risk preferences is assumed rather than measured – an approach akin to the canonical economic model of decision-making. Although standard economic models assume exogenous and stable preferences (Friedman, 1962; Stigler and Becker, 1977) overlooking the fundamental endogeneity of preferences would limit the insights that could be gained from examining household decision-making (Becker and Mulligan, 1997; Krackhardt, 1998; Netzer, 2009). "If preferences are affected by the policies or institutional arrangements we study, we can neither accurately predict nor coherently evaluate the likely consequences of new policies or institutions without taking account of preference endogeneity" (Bowles, 1998, p. 75). Therefore, ignoring the endogeneity of risk preferences restricts an empirical inquiry into a plausible mechanism through which risk management policy or programme interventions may influence households' economic decisions and outcomes.

The availability of institutions that facilitate risk bearing can be a main source of differential risk behaviour (Roumasset, 1976; Eswaran and Kotwal, 1989) and risk preferences (Palacios-Huerta and Santos, 2004; Mendola, 2007) among farmers. Empirical studies by Gloede et al. (2015) and Sakha (2019) show that the exposure of rural households to uninsured weather anomalies increases individual risk-aversion.[1] We hypothesise that farmers' access to WICI – a climate risk transfer mechanism – could be a stimulus that may have a reverse effect. As such, improving rural households' access to formal climate risk transfer mechanisms that buffer the households' livelihood from the effects of weather shocks may reduce farmers' risk-aversion. To date, empirical studies have not explored this possibility as they have focused on the effects that farmers' risk preferences have on the uptake of WICI as demonstrated in Giné et al. (2008), Cole et al. (2013), Hill et al. (2013), Karlan et al. (2014), and Jin et al. (2016).[2] However, the implicit assumption that farmers' risk preferences are exogenous and cannot be changed may be excessive (Melesse and Cecchi, 2017). Our study contributes to the literature by examining the impact of agricultural households' access to WICI on their risk-aversion, while taking into account the endogeneity of both risk preferences and WICI uptake. The sources of endogenous WICI uptake are: (i) the effect of risk preferences on WICI uptake (simultaneity bias), and (ii) the effect of unobserved heterogeneity among farmers that can simultaneously affect risk preferences and WICI uptake (self-selection bias).

Our study is set in Ethiopia, where devastating negative rainfall shocks are ubiquitous (Suryabhagavan, 2017). The study provides valuable insights into the structural relationship between a pilot programme intervention that facilitates access to WICI and farmers' risk preferences. We rely on an experimental incentive-compatible risk elicitation method, which according to Charness et al. (2013) and Meyer (2014) enables researchers to obtain an isolated measure of farmers' utility curvature parameters - risk preferences. In so doing, we analyse the impact of WICI on farmers' risk preferences and explore one of the possible causes of change in risk-aversion. Our study con-

[1] The evidence on the impact of climate shocks on individual risk preferences using cross-sectional data in Gloede et al. (2015) is consistent with the findings of Sakha (2019) that use panel data.

[2] There is a clear distinction between index- and indemnity-based insurance products in terms of how they correlate with risk preferences. Demand for index-based crop insurance is no longer necessarily increasing in risk-aversion, making it fundamentally different to that for indemnity crop insurance products (Clarke, 2016).

tributes to the small but growing literature on the effects of markets on individual risk-aversion (see section 4.2 for a review). Outside the context of markets, there are also few but growing number of empirical studies that show changes in risk-aversion due to individual's exposure to conflict and violence (Voors et al., 2012; Callen et al., 2014; Moya, 2018; Jakiela and Ozier, 2019), climate shocks and natural disasters (Eckel et al., 2009; Cameron and Shah, 2015; Gloede et al., 2015; Cassar et al., 2017; Hanaoka et al., 2018; Sakha, 2019), and financial shocks (Malmendier and Nagel, 2011; Cohn et al., 2015).

We utilise data collected from 240 smallholder farmers with access to a WICI scheme in Northern Ethiopia. Household survey data were collected from insured and uninsured agricultural households. We conducted a simple unframed risk experiment to elicit individual risk preferences using incentive compatible lotteries that involve a choice between a sure amount and a lottery with two varying pay-offs but equal probability as presented in Brick et al. (2012). We use a simultaneous equations model (SEM) and an endogenous switching probit (ESP) model to estimate the impact of WICI on the risk-aversion of farmers, after adjusting for observed covariates. Our results from the preferred model (i.e. ESP) show that there is significant positive self-selection for non-purchaser farmers. Risk-aversion and the decision not to buy WICI are perfectly correlated. We observe a negative selection effect for the purchaser farmers, but it is not statistically significant. The impact estimates show that WICI significantly decreases the risk-aversion of farmers. On average, the risk-aversion of farmers who have purchased WICI is significantly lower than what it would have been had they not purchased the insurance product. Similarly, the risk-aversion of non-purchaser farmers would have also been reduced if they had taken up WICI. Moreover, if every farmer in the study area is insured, the proportion of risk-averse farmers would decline by 35 percentage points. If WICI uptake changes risk-aversion, we should also plausibly observe that in real-life behaviour, which we do: WICI increases mineral fertilizer use. Therefore, WICI uptake can change farmers' interpretation of the operating environment for farming and ultimately reduces their risk-aversion, a major driver of agricultural technology adoption.

Our research on the endogeneity of risk preferences in relation to insurance markets is conceptually relevant to explain economic decisions of agricultural households in the presence of climate risks. The findings of our study have important implications for policy and programme interventions that intend to spur economic development in agrarian economies in the era of frequent and severe climate shocks. Since formal climate risk transfer mechanisms significantly reduce farmers' risk-aversion, investments on risk management policies and strategies can have long-term effects on agricultural households by bringing up desirable economic behaviour that may enable them to break out of poverty traps and enjoy virtuous cycle of increasing income.

The remainder of the paper is organized as follows. Section 4.2 reviews prior works that provide a link between (insurance) markets and households' preferences and behaviour. Section 4.3 describes the insurance product, and presents the source of data and methods of data analysis. Section 4.4 presents the descriptive and econometric results of the study, and the discussion based on the results. Section 4.5 concludes.

4.2 Literature

4.2.1 Agricultural households, crop insurance markets, and risk-taking behaviour

At the heart of agricultural households economic model is the issue of whether production, consumption, and labour supply decisions are simultaneously determined or if they are separable (see 1.4). In most developing countries, where markets related to factors of production, credit, insurance, and some basic commodities are non-existent or incomplete, households' production and consumption decisions are non-separable (Singh et al., 1986; Taylor and Adelman, 2003; Mendola, 2007). As such, production decisions (input use, adoption of farm technologies, and output choice) affect consumption via food production and income levels, and those production decisions are entirely independent of consumption. In the presence of climate risks, as an adaptive response, farmers usually modify their production practices to safer but low-return activities as a means of providing self-insurance to smooth consumption (Rosenzweig and Binswanger, 1993). In these circumstances, liquidity constraints generated by market imperfections shape agricultural households' decisions and behavioural responses that determine their immediate and long-term income generating capacity.

Recently, field experiments have been carried out in developing countries to estimate the causal effect of relaxing insurance market constraints on the households' tendencies to invest in agricultural activities that are risky but highly profitable. Hill and Viceisza (2012) conduct a framed field experiment in rural Ethiopia to examine farmers' decision whether to invest in mineral fertilizers or not in the presence of an insurance market. They found that farmers' uptake of the insurance product has a positive effect on fertilizer purchases. In a randomized experimental setting in rural India, Mobarak and Rosenzweig (2012) find that rice farmers that were offered the index insurance product plant less drought resistant (high-risk) but high-yield rice varieties, which may bear desirable welfare effects on these households by improving both food availability and income. Similarly, Karlan et al. (2014) randomly assigned farmers in Ghana in three treatment arms to receive cash grants, premiums to purchase rainfall index insurance, or a combination of the two. They find that farmers that purchased insurance made larger agricultural investments and risky production choices with higher expected returns. All the studies mentioned above show the impact of WICI on risk-taking in agricultural investment decisions of farmers but not on their risk preferences *per se*. Our study examines the presence of a causal relationship between farmers' access to insurance markets and their risk preferences.

4.2.2 Markets and endogenous risk preferences

The standard economic assumption of fixed and exogenously determined preferences has submerged the economic thought that the natural, social, economic, financial, and political environment may shape preferences of individuals. The assumption of exogenous and stable risk preferences implies that one should obtain the same estimate of a curvature parameter of the utility function when measuring an individual's risk preferences repeatedly. However, this has not been the case in most recent empirical studies which show systematic variations in the parameter that characterizes an individual's risk preferences (see Schildberg-hörisch (2018) for a recent review). The endogeneity of preferences implies that policies and institutional arrangements affect the evolution of tastes and values regarding consumption, investment, and other socio-economic activities (Bowles, 1998). Changes in economic institutions, such as markets, signal different stimuli to people and influence them to perceive a different world, which leads to changes in values and preferences (Bowles, 1998; Gerber and Jackson, 1993).

In this regard, Palacios-Huerta and Santos (2004) developed a general equilibrium framework to examine the endogenous formation of preferences associated with the extent of credit market completeness in Bangladesh. The primary empirical prediction of the model is that risk-aversion attitudes will be endogenously related to credit market arrangements. They used the worst floods that the country experienced in 1988 as exogenous variation, which segmented the existing micro-credit institutions, to compare individual risk attitudes during this situation and the more normal circumstances of 1992. They provide estimates of risk-aversion coefficients that are significantly lower for households where credit markets appear to be well-functioning relative to the poorly functioning counterfactual. Melesse and Cecchi (2017) use an artefactual field experiment in Ethiopia to offer insights into changes in individuals' risk preferences as a result of their exposure to output markets. Their empirical analyses reveal that farm households with greater market experience are more risk tolerant. They indicate that risk-aversion is a trait that can be endogenously changed through increasing the households' exposure to markets, and thus the claim that farm households are inherently risk-averse may be excessive. To the best of our knowledge, our study is the first empirical investigation that attempts to establish a causal relationship between farmers' access to crop insurance market and risk-aversion.

4.3 Methodology

4.3.1 Description of the WICI scheme

This study evaluates the WICI scheme in Ethiopia. The existing scheme is the continuation of the Horn of Africa Risk Transfer for Adaptation (HARITA) pilot programme which was initiated in 2009 insuring 200 households in one district in Tigray regional state of Ethiopia (Madajewicz et al., 2013). Building on the success of HARITA, the R4 rural resilience initiative emerged in 2011, bringing together a network of partners including the World Food Programme (WFP), Oxfam America (OA), Relief Society of Tigray (REST), Nyala Insurance Share Company, Africa Insurance Company, Dedebit Credit and Savings Institution (DECSI), Mekelle University, and the International Research Institute for Climate and Society (IRI) (Madajewicz et al., 2017).

The main objective of R4 is to enable farmers manage climate risks and attain food and income security. In 2017, R4 reached a total of more than 31, 942 agricultural households in 11 districts in

Tigray and 1 district in Amhara national regional states of Ethiopia (WFP/OA, 2018).[3] The crop insurance product under the R4 initiative covers major cereals (i.e. *teff*, wheat, barley, maize, and sorghum) that are widely produced in the study *Tabias*, which are the smallest administrative units within a district. Insurance enrollment usually takes place between March and June. During the survey period, farmers paid a premium of 160 ETB for a single insurance coupon that paid out on average 800 ETB. The WICI scheme also has an insurance-for-work component which allows farmers to pay their premium by providing their labour to the public works of the national safety net programme (PSNP) (Madajewicz et al., 2017).

A unique aspect of the WICI scheme under the R4 initiative is the comprehensive strategy that is implemented to handle the issue of weather-related basis risk. Basis risk is an inherent problem to index insurance such that there is a mismatch between the index-triggered payouts and the actual losses suffered by farmers. The WICI scheme has a separate R4 basis risk fund to ensure that losses are compensated for farmers in areas where the index has not adequately captured negative rainfall shocks, and these payments are made at the same time as the insurance payouts (WFP/OA, 2018). Therefore, the WICI under the R4 initiative is more risk-free than the common index-based insurance products in other developing countries. Currently, the R4 initiative expanded to reach farmers in Senegal, Malawi, Zambia, Kenya and Zimbabwe (WFP/OA, 2018).

4.3.2 Source and type of data

This study is based on data collected from farmers that reside in *tabias* with access to WICI in Tigray regional state of Ethiopia. We collected primary data from insured and uninsured rural households using a household survey and an incentivised risk experiment. A multistage random sampling method was employed to generate a total sample of 240 agricultural households. Tigray regional state has a total of 34 districts. R4 is operating in 11 districts where each district comprises of 15 to 20 *tabias*, and not all the *tabias* in the R4 districts have access to the WICI. Therefore, we take this into account in our multistage random sampling procedure. First, we randomly selected 2 districts (namely Alamata and Raya Azebo) from the list of 11 districts with some of their *tabias* having access to WICI. Then, from a total of 16 *tabias* that have access to WICI in the two districts, five (two from Alamata and three from Raya Azebo) were randomly picked. Finally, we randomly selected a total of 120 purchaser and 120 non-purchaser households from the five *tabias*. A structured questionnaire was prepared to collect socioeconomic data that focus on the demographic, agronomic and institutional variables in the 2017 farming season.

As part of the larger survey, an unframed incentivised risk experiment was also carried out individually to elicit the risk preferences of the sample farmers. Incentivised experiments are regarded as appropriate because they minimize self-serving biases, inattention, and strategic motives that distort self-reported risk attitudes (Camerer and Hogarth, 1999). This paper utilized the ex-

[3]The R4 pilot WICI scheme in Ethiopia is implemented in districts that suffer severe and frequent drought shocks. However, some of the *tabias* in the R4 districts do not have access to WICI. These *tabias* are excluded because of a mismatch between the historical drought seasons that the households reported and the satellite rainfall data (upon which the index is computed).

perimental game protocol outlined by Brick et al. (2012)[4], which allows classifying risk-aversion categories based on expected utility theory (EUT). A simple game protocol, similar to the one we used in this study, is a reliable measurement tool of risk preferences in a mostly illiterate sample (Dave et al., 2010) and adequately captures differences in individual risk preferences (Charness et al., 2013). The risk preferences elicitation experiment was administered individually after the completion of the survey.[5] The maximum possible earnings from the experiment were 20 ETB[6] with subjects receiving 11.30 ETB on average. This amount is higher than the opportunity cost of their time spent participating in the experiment and hence ensures a salient incentive for the farmers to make their decisions carefully.[7]

As depicted in Table 4.1, after a practice round, the experimenter asked each farmer to make five choices involving real money. Each choice (task) is a decision between picking a sure amount of money in option A, and tossing a coin in option B to earn either 20 ETB if the head comes up or nothing, if tail did. While farmers made decisions on five tasks, only one was randomly picked to determine their earnings. Since they could not know in advance which task will that be and each task has an equal chance of being used in the end, subjects are expected to think carefully about which option they prefer in each task. The first task is a rationality check and merely tests whether the participants understood the game. We also enforced monotonicity – if they switched they should switch from option A to option B only once. One subject, however, shifted between option A and option B multiple times. Consequently, the subject was excluded from the analysis because the range of the risk preference parameter could not be computed. Hence, we are left with a sample of 239 heads of smallholder agricultural households for our analyses.

We followed the constant relative risk-aversion (CRRA)[8] utility function to compute the range of the risk preference parameter at each task where the switch could happen. Based on these ranges, we classified the risk preferences of farm households into four categories – risk-takers, risk-neutral, risk-averse, and highly risk-averse[9]. For instance, for a given farmer who shifted from option A to option B in the second task the range of the risk preference parameter ($-1.41 < r < 0$) is computed as compound inequalities given by;

$$\frac{20^{1-r}}{1-r} > \frac{0.5\times 20^{1-r}}{1-r} \text{ and } \frac{15^{1-r}}{1-r} < \frac{0.5\times 20^{1-r}}{1-r}$$

Based on Table 3.1, our ordinal risk preferences variable entails the four risk preference categories, ordered, based on the level of risk-aversion as follows;

[4]We maintain the original design as outlined by Brick et al. (2012), but we used fewer decision tasks to make the risk elicitation experiment as simple as possible without compromising its construct validity.

[5]Appendix A in the supplementary materials presents the instruction for the risk experiment.

[6]One ETB is 0.044 U.S. Dollar based on the survey period average official exchange rate, which is obtained from OANDA currency converter `http://www.oanda.com/currency/converter`.

[7]Public works participation in the districts pays 14 ETB per day during the survey period.

[8]CRRA states that the degree of risk-aversion remains constant when both the monetary payoff of the lotteries and wealth increase proportionally. Under CRRA utility function, the range of the risk preference parameter is computed as; $u = \frac{x^{1-r}}{1-r}$.

[9]The highly risk-averse farmers are those who shifted at the 5th task or those who did not shift at all (i.e those who chose option A throughout).

Table 4.1: Experimental game tasks and elicited risk preferences

Task	Option A	Option B		Risk-preference	Risk-preference
	Sure Amount	Outcome 1	Outcome 2	parameter range	Category
1	20	20; $\frac{1}{2}$	0; $\frac{1}{2}$	$r < -1.4$	Rationality-check
2	15	20; $\frac{1}{2}$	0; $\frac{1}{2}$	$-1.41 < r < 0$	Risk-takers
3	10	20; $\frac{1}{2}$	0; $\frac{1}{2}$	$0 < r < 0.42$	Risk-neutral
4	6	20; $\frac{1}{2}$	0; $\frac{1}{2}$	$0.42 < r < 0.7$	Risk-averse
5	2	20; $\frac{1}{2}$	0; $\frac{1}{2}$	$0.7 < r$	Highly risk-averse

The last two columns are not shown or told to the subjects.

$$Risk\ preferences = \begin{cases} 1 & \text{if risk-taker} \\ 2 & \text{if risk-neutral} \\ 3 & \text{if risk-averse or highly risk-averse} \end{cases}$$

Moreover, to facilitate the estimation of treatment effects using a small sample and more flexible model specification, following Cameron and Shah (2015) and Jakiela and Ozier (2019) we converted our ordinal risk preference dependent variable into a binary variable. We framed the binary variable to indicate risk-aversion of farmers as follows;

$$Risk\ averse = \begin{cases} 1 & \text{if risk-averse or highly risk-averse} \\ 0 & \text{if risk-neutral or risk-takers} \end{cases}$$

4.3.3 Identification strategy

Using a naïve ordered probit model, the effect of WICI on the risk preferences of farmers can be estimated by regressing the latent variable representing the propensity of risk-aversion of farmer *i* (Y_i^*) on the WICI uptake of the farmer (T_i) and a vector of household characteristics (x_i) assuming exogenous WICI uptake – the correlation between the error term (ω_{1i}) and T_i is zero. α and β_1 are unknown parameters to be estimated.

$$Y_i^* = \alpha T_i + x_i \beta_1^{'} + \omega_{1i},\ \omega_1 \sim \mathcal{N}(0, \sigma^2) \tag{4.1}$$

where the subscripts indicate variation over farmers (i = 1, 2, ..., N). The latent risk-aversion variable (Y_i^*) and thresholds (η_1 and η_2) are not directly observed. Instead, we only observe

$$Y_i = \begin{cases} 1 & \text{if } Y_i^* \leq \eta_1 \\ 2 & \text{if } \eta_1 < Y_i^* \leq \eta_2 \\ 3 & \text{if } Y_i^* > \eta_2 \end{cases}$$

For this study, however, the assumption of exogenous WICI uptake decision of farmers is unrealistic due to self-selection and simultaneity biases. Hence, the ordered probit specification may result in biased estimates on the causal effect of purchasing WICI on the level of risk-aversion of farmers. To address the problem of endogeneity in equation 4.1, we use a maximum likelihood estimator of an ordinal outcome with a binary endogenous regressor under the simultaneous equations model (SEM). Maximum likelihood estimators have the properties of being consistent and asymptotically efficient (Greene, 2012). The SEM jointly determines equations 4.1 and 4.2 as a system of two equations that allows risk preferences to be correlated with the binary WICI uptake choice in equation 4.2, and WICI uptake to be an endogenous regressor in the ordinal risk preferences outcome variable in equation 4.1. This enables us to estimate the coefficient on T_i (α) as the unbiased measure for the average treatment effect (ATE) – the average effect of changing the whole population from being non-purchasers to purchasers of WICI. The binary endogenous WICI uptake is modeled as;

$$T_i^* = x_i\beta_2^{'} + \gamma Z_i + \omega_{2i},\ \omega_2 \sim \mathcal{N}(0, \sigma^2) \tag{4.2}$$

where, the i^{th} farmer's propensity to purchase WICI (T_i^*) is a latent continuous variable for which only the binary variable T_i is observed such that;

$$T_i = \begin{cases} 0 & \text{if } T_i^* \leq 0 \\ 1 & \text{if } T_i^* > 0 \end{cases}$$

where x_i is a vector of variables identical to the one in equation 4.1 and Z_i is an instrumental variable (IV). The SEM model is generally identified even in the absence of the excluded variable (Z_i). However, to improve identification we used a binary variable that indicates whether farmers live in the same village with the insurance foreman as the excluded variable from equation 4.1. Nigus et al. (2018) used a similar IV in their analysis on the effect of WICI on social capital. The rationale behind choosing this IV is that the insurance foremen are tasked for promoting and creating awareness among farmers about WICI. We, therefore, hypothesized farmers are likely to have better knowledge and attitudes about WICI if the foreman lives in the village they belong to, and ultimately influence their decision to opt for the insurance uptake. Moreover, the assignment of the foremen are an administrative level decision, independent of households' risk behaviour. α, γ, β_1 and β_2 are unknown parameters to be estimated. $(\omega_{1i}, \omega_{2i})'$ is a vector of error terms that follows a bivariate standard normal distribution with correlation coefficient ρ described as;

$$\begin{pmatrix} \omega_{1i} & \omega_{2i} \end{pmatrix}' \sim \mathcal{N}\left(\begin{pmatrix} 0 & 0 \end{pmatrix}', \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}\right)$$

We also used a full information maximum likelihood (FIML) under the endogenous switching probit (ESP) model to take into account the interdependencies between WICI uptake and separate equations for the outcome variables (i.e. risk-aversion and mineral fertilizer use) of purchasers and non-purchasers. ESP is a more flexible specification than SEM since it allows the effects of household characteristics on the outcome variables to vary between the purchaser and non-purchaser farmers. Consequently, besides the ATE, we can also estimate the average treatment effect on the treated (ATT) and average treatment effect on the untreated (ATU). The ATT is the average effect of WICI on those farmers who have purchased the insurance. The ATU is the average effect of WICI on the risk-aversion of non-purchasers had they decided to uptake the insurance.

The ESP model simultaneously considers a binary outcome variable - risk-aversion or fertilizer use - that describes the behaviour of farmers with two regimes (equations 4.3 and 4.4) and a switch (selection) function (equation 4.2) that determines which regime the farmer faces. Along with equation 4.2, the ESP can be specified as a system of equations for latent variables as;

$$Y_{1i}^{*} = x_{1i}\tau_1^{'} + \varepsilon_{1i} \tag{4.3}$$

$$Y_{0i}^{*} = x_{0i}\tau_0^{'} + \varepsilon_{0i} \tag{4.4}$$

where the observed farmer's WICI uptake decision is as defined under equations 4.2. $Y_1 i^*$ and $Y_0 i^*$ are the latent variables for the binary outcome variable of the purchasers and non-purchasers respectively. The observed Y_i is defined as:

$$Y_i = \begin{cases} Y_{1i} & \text{if } Y_{1i}^{*} > 0 \; and \; T_i = 1 \\ Y_{0i} & \text{if } Y_{0i}^{*} > 0 \; and \; T_i = 0 \end{cases}$$

Moreover: x_{1i} and x_{0i} are vectors of explanatory variables; γ, β_2, τ_1 and τ_0, are unknown parameters to be estimated; and ω_{2i}, ε_{1i}, and ε_{0i} are the error terms which are jointly normally distributed with a mean-zero vector and correlation matrix:

$$\Omega = \begin{pmatrix} 1 & \rho_0 & \rho_1 \\ & 1 & \rho_{10} \\ & & 1 \end{pmatrix}$$

where ρ_0, ρ_1 and ρ_{10} are the correlations between ε_0 and ω_2, ε_1 and ω_2, and ε_1 and ε_0 respectively. While ρ_{10} can not be estimated, ρ_0 and ρ_1 are identified since the data provide information on the correlations (Miranda and Rabe-Hesketh, 2006). If $\rho_0 \neq \rho_1 \neq 0$, treating WICI as an exogenous variable delivers inconsistent estimator because WICI uptake decision is correlated with ε_0 and ε_1 (Huang et al., 1991). As such, ρ_0 and ρ_1 capture the extent to which risk-aversion affects WICI uptake decision of non-purchasers and purchasers, respectively.

The ESP analysis also does not require exclusion restrictions to identify treatment effects since the model can be identified by the non-linearities in the inverse mills-ratio using two-step estimation method (Heckman, 1978). As a consequence, ESP model can be estimated without Z_i such that x_i, x_{1i} and x_{0i} contain identical elements. However, Maddala (1983) noted that specifying at least one exclusion restriction better identify the selection mechanism and FIML estimation method is more efficient than two-step estimation procedures to estimate ESP. To that end, we used the binary variable that captures whether the foreman lives in the same village with the household as the excluded variable from the vectors x_{1i} and x_{0i}. Following Aakvik et al. (2005) and Lokshin and Sajaia (2011), after estimating the parameters of the ESP model using FIML method, we can compute endogeneity-bias corrected estimates of the variant treatment effect measures − ATT (equation 4.5), ATU (equation 4.6), and ATE (Equation 4.7) − as:

$$\begin{aligned} ATT &= E\left[Pr(Y_1 = 1 \mid T = 1, X = x)\right] - E[Pr(Y_0 = 1 \mid T = 1, X = x)] \\ &= E\left[\frac{\Phi_2(x_1\tau_1, Z\gamma, \rho_1) - \Phi_2(x_0\tau_0, Z\gamma, \rho_0)}{F(Z\gamma)}\right] \end{aligned} \tag{4.5}$$

$$\begin{aligned} ATU &= E[Pr(Y_1 = 1 \mid T = 0, X = x)] - E[Pr(Y_0 = 1 \mid T = 0, X = x)] \\ &= E\left[\frac{\Phi_2(x_1\tau_1, -Z\gamma, -\rho_1) - \Phi_2(x_0\tau_0, -Z\gamma, -\rho_0)}{F(-Z\gamma)}\right] \end{aligned} \tag{4.6}$$

$$\begin{aligned} ATE &= E[Pr(Y_1 = 1 \mid T = 1, X = x)] - E[Pr(Y_0 = 1 \mid T = 0, X = x)] \\ &= E\left[F(x_1\tau_1) - F(x_0\tau_0)\right] \end{aligned} \tag{4.7}$$

where Φ_2 is the cumulative function of a bivariate normal distribution and F is the cumulative function of a univariate normal distribution.

4.4 Results and Discussion

4.4.1 Descriptive statistics

The experimental results show that 39 percent of farmers in the study area are risk-averse. Our estimate is comparable to the findings of a recent study by Jin et al. (2017) who used similar risk preference elicitation experimental games and found that 44 percent of the households in rural China are risk-averse. Table 4.2 depicts the mean values for the continuous variables and mean proportions for the binary variables under the two groups – purchasers and non-purchasers of WICI. We used the independent t-test to assess whether the mean values or proportions of a given variable vary across the two groups of households.

The averages show that non-purchasers are less risk-averse than purchaser farmers. A significantly larger proportion of purchasers live in the same village with the insurance foreman. On average, the purchaser households have a higher number of economically active members than their non-purchaser counterparts. The average land and livestock holdings of the non-purchasers are significantly higher than that of the purchasers. With regard to access to credit and ownership of television or radio, on average, the purchaser farmers are better off than the non-purchasers. A

Table 4.2: Mean and mean difference tests of the variables included in the analyses

Variables	Non-purchasers (N=119) Mean	Purchasers (N=120) Mean	t-test Mean Diff.
Variables of interest			
Risk preferences			
risk-taker	0.479	0.400	0.079
risk-neutral	0.193	0.150	0.043
risk-averse	0.328	0.450	-0.122*
Mineral fertilizers use	0.351	0.342	0.009
Same village with insurance foreman	0.361	0.733	-0.372***
Control variables			
age	39.66	41.53	-1.88
sex	0.824	0.742	0.082
education	0.378	0.408	-0.030
active people	2.403	3.042	-0.638***
asset holding[a]	15.06	15.76	-0.70
tropical livestock unit[b]	5.778	4.264	1.514***
land holding	1.330	1.102	0.228**
housing condition	0.807	0.792	0.015
access to credit	0.714	0.817	-0.102*
private transfer	0.445	0.342	0.104
cooperative member	0.723	0.675	0.048
iddir member[c]	0.950	0.975	-0.025
equb member[c]	0.471	0.442	0.029
ties with training office	0.101	0.642	-0.541***
own TV or radio	0.269	0.467	-0.198***
own phone	0.773	0.733	0.040

Notes: Appendix Table A4.1 in the supplementary materials presents the full description of each variable.
[a] Asset holding is an index (scaled between 0 and 100) constructed based on binary variables indicating the household's ownership of; stove, television, radio, telephone, fridge, and drip-irrigation equipment. [b] We measured livestock holding using Tropical Livestock Unit (TLU) based on Jahnke (1982) conversion factors as Camel 1.0; horse 0.8; cattle and mule 0.7 each; donkey 0.5; pig 0.2; sheep and goat 0.1 each; and chicken 0.01. [c] Self-help groups, which are widely prevailing informal institutions in Ethiopia.

significantly higher proportion of the purchasers have personal ties with someone who works at the training and development office of the R4 WICI project.

4.4.2 Estimation results

The selection equation (farmers' WICI purchase decision) and the outcome equation(s) (farmers' risk-aversion) of the SEM and ESP models are estimated simultaneously. To facilitate detailed discussion, the results from the selection and outcome models are presented separately in the following sub-sections.

(a) Selection model – Demand for WICI

Our analyses are based on a sample of purchasers and non-purchasers that reside in *tabias* where the WICI scheme exists. Table 4.3 presents the estimation results on the selection (WICI uptake) equation after adjusting for the effects of observable and unobservable heterogeneity. We find a robust positive effect of living in the same village with the foreman (our instrumental variable) on the probability of farmers' WICI uptake. The ESP is our preferred model for the reasons described in section 4.4.2, and we discuss the results from column (2) in Table 4.3. The results show that farmers who live in the same village with the insurance foreman have 17 percentage points higher probability of purchasing WICI. A falsification test proposed by Di Falco et al. (2011) was executed to establish the admissibility of our instrument. Our IV does not enter as a statistically significant variable when included in a probit regression on the risk-aversion of non-purchaser farmers (Appendix Table A4.2 in the supplementary materials).

The average marginal effects (AME) for the remaining variables in the selection equation, i.e. the effects of changes in variables on the probability of WICI uptake, are also shown in Table 3 next to each coefficient estimate.[10] Households with a larger number of economically active family members have a higher probability of WICI uptake. Household income is an increasing function of economically active family members Manlagñit (2004) that may avail more financial resources for agricultural investments such as the purchase of WICI. Farmers' demand for WICI increases with their access to credit. Credit relaxes the households' liquidity constraints, and hence can significantly increase the probability that households purchase WICI. This result is similar to the findings of Giné et al. (2008) in rural India and Hill et al. (2013) in rural Ethiopia. The positive effect of *iddir* membership on the households' demand for WICI in Ethiopia is also documented in studies by Dercon et al. (2014) and Berg et al. (2017).

Farmers that have ties with a person who works in the training office of the R4 WICI initiative are more likely to purchase WICI. This may be due to the person's role in familiarizing a farmer about the existing agricultural risk management technology in the study area. In particular, farmers' contact with the training personnel can facilitate the flow of information that could positively

[10] The coefficient estimates on our control variables are merely correlational and could only serve as suggestive results for further inquiry. Hence, we are interested only in the direction of the associations.

Table 4.3: Selection model: Purchase of WICI

Variables	(1) SEM Probit (WICI uptake) Coeff.	AME	(2) ESP Probit (WICI uptake) Coeff.	AME
same village with foreman	0.8021***	0.1808***	0.7439***	0.1665***
	(0.2054)	(0.0433)	(0.2357)	(0.0497)
age	0.0265	0.0060	0.0175	0.0039
	(0.0163)	(0.0037)	(0.0168)	(0.0037)
sex	-0.2644	-0.0596	-0.2531	-0.0566
	(0.2679)	(0.0603)	(0.2872)	(0.0638)
education	0.2248	0.0507	0.1893	0.0424
	(0.2156)	(0.0493)	(0.3055)	(0.0684)
active people	0.1294*	0.0292*	0.1545*	0.0346*
	(0.0729)	(0.0161)	(0.0890)	(0.0201)
asset holding	-0.0041	-0.0009	0.0002	0.0001
	(0.0111)	(0.0025)	(0.0108)	(0.0024)
tropical livestock unit	-0.0829*	-0.0187**	-0.1120***	-0.0251***
	(0.0434)	(0.0095)	(0.0293)	(0.0063)
land holding	-0.2703*	-0.0609*	-0.2357	-0.0527
	(0.1583)	(0.0357)	(0.1528)	(0.0346)
housing condition	0.0772	0.0174	0.2024	0.0453
	(0.3019)	(0.0680)	(0.2663)	(0.0596)
access to credit	0.4014*	0.0905*	0.4649*	0.1040*
	(0.2311)	(0.0519)	(0.2429)	(0.0541)
private transfer	0.0080	0.0018	0.0917	0.0205
	(0.2726)	(0.0614)	(0.2507)	(0.0560)
cooperative member	-0.6758**	-0.1524***	-0.5734**	-0.1283**
	(0.2696)	(0.0578)	(0.2478)	(0.0537)
iddir member	1.0999	0.2480	1.6156**	0.3615**
	(0.9376)	(0.2078)	(0.6988)	(0.1507)
equb member	0.2085	0.0470	0.2442	0.0546
	(0.2523)	(0.0563)	(0.3050)	(0.0682)
ties with training office	1.9116***	0.4310***	2.0568***	0.4602***
	(0.2996)	(0.0447)	(0.3222)	(0.0555)
own TV or radio	0.2298	0.0518	0.0222	0.0050
	(0.3193)	(0.0720)	(0.2828)	(0.0633)
own mobile phone	-0.1732	-0.0390	-0.1613	-0.0361
	(0.2974)	(0.0667)	(0.3155)	(0.0702)
Constant	-2.6104***		-2.9502***	
	(0.9843)		(0.9083)	
Observations	239		239	

Notes: Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
SEM, ESP and AME stand for simultaneous equations model, endogenous switching probit and average marginal effect respectively.

shape their knowledge and attitudes towards WICI, and ultimately may affect their decision to purchase WICI. However, we cannot rule out the possible effect of WICI uptake on the ability of farmers to meet and know people who work in the project. On the contrary, the number of livestock owned and cooperative membership are negatively and significantly correlated with farmers' WICI uptake. Households with more livestock can rely on the sale of their livestock to buffer the effects of climate shocks Sango et al. (2007), and so they may opt against the uptake of WICI. The negative correlation between farmers' membership to a cooperative organization and WICI uptake may imply that farmers consider cooperatives as a substitute for purchasing insurance.

(b) Risk-aversion model

Our outcome variable takes the form of either an ordinal risk preferences variable ordered in accordance with farmers' levels of risk-aversion or a binary variable coded as 1 to represent risk-aversion and 0 otherwise (see section 4.3.2). The SEM and ESP estimations were used to estimate the binary WICI uptake and the ordinal or binary risk-aversion equations simultaneously. The ESP is our preferred model for two main reasons. First, the likelihood ratio test of independence between the selection and outcome equations shows that SEM is not a relevant specification for our data. Second, the Wald test rejects the joint independence of the risk-aversion equations in the two regimes and the selection model. The test provides evidence that the naïve ordered probit or probit estimates (reported in Appendix Table A4.4) are biased and inconsistent due to the presence of unobserved factors affecting the selection process and farmers' risk-aversion simultaneously. Moreover, the test also reveals that ESP is more appropriate model specification than describing the behaviour of all farmers with a single risk-aversion equation – as it is the case under SEM. Therefore, to economize space, we only discuss the results from the ESP model.

In the risk-aversion (outcome) equations for the two regimes (purchasers and non-purchasers), there are a few variables that significantly correlate with farmers' risk preferences (Table 4.4). As a formal and informal means of relaxing liquidity constraints, purchaser households' access to credit and *equb* are negatively correlated with their risk-aversion. The positive correlation between agricultural landholding and risk-aversion is observed under both regimes. In addition, risk-aversion of the non-purchasers and asset holdings are also positively correlated. Land and asset holdings are proxies for wealth and income-generating capacity of rural households. A positive correlation between income and risk-aversion of households is also presented in Bosch-Domènech and Silvestre (2006). Households' personal ties with the training personnel of the WICI scheme and ownership of radio or television – proxies for the households' access to information – are negatively correlated with risk-aversion of the non-purchasers group. The other covariates do not enter as significant predictors in the risk-aversion equations of the purchaser and non-purchaser farmers.

Table 4.4: Effect estimates for the covariates under the risk-aversion equations

Variables	(1) SEM Ordered Probit (Risk preferences)				(2) ESP Probit (Risk-aversion)	
		Average Marginal Effect (AME)			Purchasers	Non-purchasers
	Coeff.	Risk-taking	Risk-neutral	Risk-aversion	Coeff.	Coeff.
purchase WICI	-0.1639	0.0597	-0.0017	-0.0580		
	(1.7387)	(0.6320)	(0.0175)	(0.6146)		
age	0.0104	-0.0038	0.0001	0.0037	-0.0018	-0.0167
	(0.0139)	(0.0050)	(0.0002)	(0.0049)	(0.0194)	(0.0154)
sex	-0.0099	0.0036	-0.0001	-0.0035	0.1757	-0.1108
	(0.2494)	(0.0908)	(0.0026)	(0.0882)	(0.4175)	(0.3429)
education	0.0803	-0.0293	0.0008	0.0284	0.1399	-0.1159
	(0.1860)	(0.0676)	(0.0022)	(0.0657)	(0.3391)	(0.2663)
active people	0.0876	-0.0319	0.0009	0.0310	0.1477	-0.0735
	(0.0600)	(0.0213)	(0.0011)	(0.0209)	(0.0899)	(0.0721)
asset holding	0.0049	-0.0018	0.0001	0.0017	-0.0042	0.0386***
	(0.0091)	(0.0033)	(0.0001)	(0.0032)	(0.0112)	(0.0145)
tropical livestock unit	-0.0302	0.0110	-0.0003	-0.0107	0.0084	0.0178
	(0.0400)	(0.0143)	(0.0005)	(0.0140)	(0.0640)	(0.0302)
land holding	0.1487	-0.0541	0.0016	0.0526	0.3484*	0.2678*
	(0.1569)	(0.0578)	(0.0028)	(0.0556)	(0.2093)	(0.1585)
housing condition	-0.1073	0.0391	-0.0011	-0.0380	-0.0560	-0.1067
	(0.2182)	(0.0794)	(0.0027)	(0.0771)	(0.3725)	(0.2782)
access to credit	-0.5262*	0.1916*	-0.0055	-0.1861*	-0.8426**	-0.1938
	(0.2713)	(0.1000)	(0.0078)	(0.0952)	(0.3640)	(0.2754)

Table 3.4: Continued

Variables	(1) SEM Ordered Probit (Risk preferences)				(2) ESP Probit (Risk-aversion)	
		Average Marginal Effect (AME)			Purchasers	Non-purchasers
	Coeff.	Risk-taking	Risk-neutral	Risk-aversion	Coeff.	Coeff.
private transfer	0.0429	-0.0156	0.0005	0.0152	0.3215	-0.1995
	(0.1688)	(0.0615)	(0.0018)	(0.0597)	(0.3058)	(0.2487)
cooperative member	0.1077	-0.0392	0.0011	0.0381	0.2579	0.2287
	(0.4147)	(0.1516)	(0.0050)	(0.1468)	(0.3442)	(0.2802)
iddir member	0.0603	-0.0220	0.0006	0.0213	-0.6984	-0.2619
	(0.5895)	(0.2144)	(0.0061)	(0.2084)	(1.0722)	(0.5744)
equb member	-0.2570	0.0936	-0.0027	-0.0909	-0.6361**	-0.3840
	(0.2566)	(0.0944)	(0.0046)	(0.0909)	(0.3220)	(0.2742)
ties with training office	0.5394	-0.1964	0.0057	0.1908	0.2331	-0.6350*
	(1.0368)	(0.3732)	(0.0101)	(0.3651)	(1.3863)	(0.3541)
own TV or radio	-0.2505	0.0912	-0.0026	-0.0886	-0.2023	-1.0390***
	(0.2272)	(0.0828)	(0.0040)	(0.0802)	(0.3253)	(0.3234)
own mobile phone	0.0061	-0.0022	0.0001	0.0021	-0.3848	0.0533
	(0.2321)	(0.0845)	(0.0024)	(0.0821)	(0.3685)	(0.3700)
Constant					0.7835	-0.0015
					(2.6599)	(0.7831)
rho (ρ_i)	0.0916				-0.4714	-1***
	(1.0999)				(1.3241)	(2.43E-11)
Observations	239				239	
Test of $\rho_i = 0$ (p value)	0.934				0.045	

Notes: Robust standard errors in parentheses.

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

SEM, ESP and AME stand for simultaneous equations model, endogenous switching probit and average marginal effect respectively.

We used Stata commands developed by Roodman (2011) and Lokshin and Sajaia (2011) for the simultaneous equations model (SEM) and endogenous switching probit (ESP) analyses, respectively.

Tests of joint independence (p values) are based on the likelihood ratio and Wald tests under the SEM and ESP models respectively.

The error terms in the equations determining the uptake of WICI and farmers' risk-aversion of the non-purchasers are perfectly negatively correlated (ρ_0 = -1) and statistically significant. The correlation among the error terms in the selection equation and the risk-aversion model of the purchasers (ρ_1) is also negative but it is not statistically significant. These findings imply that self-selection exists only for the non-purchaser farmers. Non-purchaser farmers are significantly more risk-averse than a potentially random sample.[11]

(c) The effect of WICI on risk-aversion

Table 4.5 reports the ATT, ATU, and ATE estimates, derived from the ESP model as described in equations 4.5, 4.6 and 4.7, respectively. Purchaser farmers are on average 43 percentage points less likely to be risk-averse compared with the counterfactual scenario of non-purchaser farmers. This translates to a reduction in the risk-aversion of the purchasers by around 50 percent compared with what it would have been had they not purchased WICI. The non-purchaser farmers would have also attained, on average, 26 percentage points reduction in their risk-aversion if they had taken up WICI. This translates to a 79 percent decline in the probability of risk-aversion from the initial sub-population of risk-averse farmers in the non-purchasers group. Moreover, the average risk-aversion of farmers would have been lowered by 35 percentage points had all farmers in the study area decided to purchase the insurance product. Put differently, if the insurance scheme had covered every farmer in the study area, the probability of risk-aversion would have been around 90 percent lower compared with the counterfactual scenario of none of the farmers had purchased WICI. If we do not take into account the simultaneity and self-selection biases in analysing the impact of WICI uptake on farmers' risk-aversion, we will have a perversely signed average treatment effect estimate (Appendix Table A4.4 in the supplementary materials).

The WICI improves households' economic outcomes since the insurance payouts during negative rainfall shocks can stabilize income and ensure smooth consumption (Janzen and Carter, 2018). As a crucial determinant of economic outcomes, markets dictate the formation of values, tastes and preferences by affecting what individuals must do or be to sustain their livelihood (Gerber and Jackson, 1993; Bowles, 1998; Palacios-Huerta and Santos, 2004; Melesse and Cecchi, 2017). In the absence of crop insurance markets, farmers will "self-insure" (Rosenzweig and Binswanger, 1993), which may lead to formation of risk-averse attitudes. As such, WICI uptake may change farmers' interpretation of the operating environment for farming and ultimately reduces their risk-aversion. This also has implications on the future uptake of WICI by farmers. Our study and studies by Giné et al. (2008) and Hill et al. (2013) find that demand for index-based crop insurance product is low among risk-averse individuals, which is contrary to that for indemnity crop insurance products (Clarke, 2016). Therefore, in the context where there is uninterrupted access to index-based crop insurance market, purchasers are more likely to continue buying the insurance

[11] Without addressing endogeneity concerns, risk-aversion has a positive effect on WICI uptake and may compel us to state that more risk-averse farmers are likely to purchase WICI (Appendix Table A4.3 in the supplementary materials).

product in the future due to them having lower risk-aversion. However, in the event that access to WICI market is interrupted due to termination of the R4 initiative or other external shocks, we cannot rule out the possibility that the reduction in farmers' risk-aversion is reversible as farmers may revert to "self-insurance".

Table 4.5: Treatment effect estimates: Impact of WICI on risk-aversion

Treatment effect estimates	Observations	Estimate
Average Treatment Effect on the Treated (ATT)	120	-0.4267***
		(0.0221)
Average Treatment Effect on the Untreated (ATU)	119	-0.2620***
		(0.0235)
Average Treatment Effect (ATE)	239	-0.3506***
		(0.0160)

Notes: Standard errors in parentheses. *** $p<0.01$
We used the Stata command developed by Lokshin and Sajaia (2011) for estimating the treatment effects.

(d) The effect of WICI on observed risk-taking behaviour

In this section, we examine to what extent the effect of WICI on farmers' risk-aversion is translated into their economic risk-taking behaviour in daily life. We use the decision to apply mineral fertilizers as an observed risk-taking behaviour of farmers. Since the early work by Rosenzweig and Binswanger (1993), it has been shown that farmers in developing countries employ a self-insurance mechanism by avoiding high-risk high-return agricultural technologies to minimize income variability. Mineral fertilizers perfectly match the definition of high-risk high-return agricultural technologies. According to Fosu-Mensah and Mensah (2016), a profound yield-enhancing effect of mineral fertilizers is realized in soils with sufficient moisture. In the context of rainfed agriculture, their finding may mean that the desirable yield- and income-boosting effects of mineral fertilizers are associated with the presence of favourable weather conditions during the agricultural season. Otherwise, households may not recover what they spend to purchase mineral fertilizers in the presence of insufficient and more variable rainfall (Alem et al., 2010). Therefore, in an environment characterised by erratic weather conditions, taking farmers' decision to adopt mineral fertilizer as our outcome variable enables us to examine whether WICI uptake has a positive effect on farmers' risky but profitable agricultural investment decisions. Our binary outcome variable for fertilizer use takes the value of 1 if the farmer used mineral fertilizers during the production year in the survey period, and 0 otherwise.

The positive and statistically significant impact of WICI on the adoption of mineral fertilizer matches our expectation.[12][13] Table 4.6 shows that the likelihood of mineral fertilizer use by pur-

[12] This finding is also in line with previous studies by Hill and Viceisza (2012), Mobarak and Rosenzweig (2012), and Karlan et al. (2014) that show the causal effect of insurance on household decision to invest in risky but highly profitable agricultural activities.

[13] The parameter estimates of the ESP model are reported in Table A4.5 in the supplementary materials.

chasers of WICI increased by 60 percentage points. Similarly, the adoption rate of non-purchasers would have increased by 33 percentage points if they had taken-up WICI. These findings imply that the magnitude of the impact of WICI on the application of mineral fertilizer is larger for purchaser farmers. Insuring all farmers in the study area would have increased the probability of mineral fertilizer application by 46 percentage points compared to the scenario where none of the households had purchased WICI. In this case, the adoption rate of mineral fertilizers in the study area would have been increased to 81 percent.[14] Our results show that farmers who purchased WICI are more likely to benefit from favourable agricultural seasons above and beyond non-purchasers because of their investments in yield-boosting agricultural technologies. Changes in risk-aversion may be a plausible mechanism through which WICI uptake causes an effect on farmers' risk-taking behaviour in their agricultural investment decisions − proxied by adoption of mineral fertilizers.

Table 4.6: Treatment effect estimates: Impact of WICI on mineral fertilizers use

Treatment effect estimates	Observations	Estimate
Average Treatment Effect on the Treated (ATT)	120	0.5958***
		(0.0249)
Average Treatment Effect on the Untreated (ATU)	119	0.3295***
		(0.0226)
Average Treatment Effect (ATE)	239	0.4617***
		(0.0159)

Notes: Standard errors in parentheses. *** $p<0.01$
We used the Stata command developed by Lokshin and Sajaia (2011) for estimating the treatment effects.

We also examine the relative importance of farmers' WICI uptake, risk preferences and other observable characteristics in predicting their decision to adopt mineral fertilizer.[15] This endeavor allows us to explore whether WICI uptake is more important in predicting mineral fertilizer adoption than farmers' risk preferences.[16] In such a scenario, risk-aversion may have little importance in explaining the impact of WICI on fertilizer adoption. Appendix Figure 1.1 depicts the ranks of observed variables based on their relative importance in predicting farmers' decision to use mineral fertilizer.[17] Our result supports previous findings by Liu (2013), Ward and Singh (2015), Brick and Visser (2015), and Holden and Quiggin (2017), who show that risk preferences are the most important drivers of agricultural technology adoption. The importance of WICI uptake in predicting household decision to use mineral fertilizer is lower than the relative importance of farmers' risk preferences. Taking into account the results in the preceding section, our findings suggest that WICI uptake influences household decisions to adopt agricultural technologies mainly through

[14]If our analysis had not considered self-selection bias, the effect of WICI on mineral fertilizer use would have appeared to be negatively signed (Appendix Table A4.6 in the supplementary materials).
[15]The random forest (RF) method, which we used for the analysis, is explained in Appendix B.
[16]We thank the anonymous reviewer for this insightful suggestion.
[17]Future studies that generate experimental panel data may facilitate mediation analyses and provide the point estimates on the impact of the predictors presented in Appendix Figure A4.1.

its effect on risk preferences. Hence, risk preferences are influenced by crop insurance market arrangements where farmers operate. In turn, risk preferences determine household decisions to invest in high-risk but profitable agricultural technologies.

4.5 Conclusion

In the presence of uninsured climate risks, farmers in developing countries acquire their livelihood by engaging in low-risk low-return practices to provide "self-insurance" (Rosenzweig and Binswanger, 1993), which may lead to formation of risk-averse attitudes. This economic behaviour permanently keeps them in low-income low-investment vicious cycle (Carter and Barrett, 2006; Dercon and Christiaensen, 2011). One focus area of active research has been analysing how preferences are formed and change in the presence of external stimuli. There has been a long-standing argument about the importance of policies and institutions in shaping households' risk behaviour (Roumasset, 1976; Eswaran and Kotwal, 1989) and risk preferences (Bowles, 1998; Palacios-Huerta and Santos, 2004; Mendola, 2007). However, in the context of formal climate risk transfer mechanisms, previous studies that examined the relationship between the uptake of WICI and real-life risk-taking behaviour of farmers considered risk preferences as given, which restricts an empirical inquiry into change in risk preferences as a plausible mechanism. By taking the case of Ethiopia, this study contributes to the existing literature on the causes of change in risk preferences by providing valuable insight into the structural relationship between a programme intervention that facilitates access to WICI and farmers' risk-aversion.

Empirically isolating the causal effect of farmers' WICI uptake on their risk-aversion using observational data is a challenging task. Simultaneity bias – risk-aversion of farmers determine their WICI uptake decision – and self-selection bias – the presence of unobserved farmer characteristics that affect both WICI uptake and risk-aversion - are serious concerns. We used the ESP model to address these concerns. Our results from the selection equation show that promotion and training officers of WICI can play a significant role in getting farmers to take-up the insurance product. The treatment effect estimates provide evidence for a significant reduction in the risk-aversion of farmers in response to the uptake of WICI.

We find that farmers who purchased WICI are less likely to be risk-averse compared to non-purchaser farmers. Similarly, non-purchasers would have attained a significant reduction in their risk-aversion if they had taken up the insurance product. Overall, if the insurance scheme had covered every farmer in the study area, the probability of risk-aversion would have been around 90 percent lower relative to the counterfactual scenario where none of the farmers had purchased WICI. We also find that WICI has a positive and statistically significant effect on farmers' real-life risk taking behaviour - mineral fertilizer use. We argue that WICI uptake reduces farmers' risk-aversion by plausibly changing their interpretation of the operating environment for farming. In turn, changes in farmers' risk-aversion is arguably a major channel through which WICI uptake influences their investment decisions on high-risk high-return agricultural technologies.

Our study contributes to evidence-informed policymaking that intends to spur economic growth in developing countries in the era of frequent and severe climate shocks. Risk preferences are linked to economic development by influencing households' production, consumption and labour supply decisions that, in turn, determine the accumulation of human, physical and financial capital. The role of climate risk management policies in general and WICI in particular in the poverty alleviation and economic development can also be channelled through their effects on risk preferences. Thus, investments on policies and strategies aiming to improve farmers' access and uptake of formal climate risk transfer mechanisms can have long-term effect on the development prospects of agrarian economies by bringing up desirable individual economic behaviour that may enable households to break out of poverty traps and enjoy virtuous cycle of increasing income.

Since our analyses are based on cross sectional data, we can assess only the variation in risk-aversion of a given farmer in relation to WICI uptake at a given point in time. There is a need for further investigation on the within-farmer effects of WICI uptake on risk-aversion using panel data. In so doing, one can robustly identify whether the observed change in farmers' risk-aversion in relation to purchase of WICI is attributed to change in the risk preference of a given farmer across time. Furthermore, the special basis-risk fund of the WICI scheme under the R4 initiative, which we have evaluated in this study, makes it distinct from the common index-based insurance products that do not have such a feature. Future research on the impact of WICI without the basis-risk fund on farmers' risk-aversion would show the generalisability of our findings. Moreover, comparative assessments on the adoption and impact of WICI with and without the basis risk fund would also be insightful concerning the identification of effective and efficient design feature of the insurance product.

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Appendix A4

Appendix A4.1 Instructions for the risk experiment

Thank you for participating in this experimental game, which involves decision-making. I want to make some general explanations about what we will be doing now and the rules of the game. Of course, you have every right to cease your participation in the experiment at any time if it makes you feel uncomfortable or do not want to stay any longer for any reason.

You will be asked to make several choices involving real money. Each choice is a decision involving picking between two options. Your decision sheet shows five choice tasks that require you to make a choice by ticking in the relevant box (I will assist you in marking your choice). Even though you will make five decisions, only one of your choices will be randomly picked at the end to determine your earnings. So, you should think carefully about which option you prefer in each decision task since each decision has an equal chance of being used in the end. Whatever money you win in the experiment will be yours to keep and take home. If you have any questions or doubts, do not hesitate to ask me.

For each row (decision task) in Table 4.1, you will be asked to choose between whether you would prefer to receive a sure amount (option A) or play a lottery with two outcomes having equal chance of occurring (option B), which remains unchanged throughout the choice tasks. The sure amount offered under option A will decline in magnitude in successive choices. Option B involves tossing a coin to earn either 20 ETB if the head comes up or nothing if the tail did. You are free to choose either only one of the options for the entire choice tasks or switch from one option to the other at any row. If you choose to switch, you should switch only once and pick that option for the rest of the decision tasks. For instance, if you switch from option A to option B in the second row, you will also pick option B in the third, fourth and fifth rows. If you switch from option A to option B in the third row, you will also choose option B in the fourth and fifth rows, and so on. After careful completion of your choices, there will be a random selection of the choice task that will give the actual payout. In general, there is no good or bad decision in each choice task, because one option is not necessarily better than the other. Which option you prefer in each choice task is a matter of personal preference. All your answers to the choice tasks will be private, and cannot be traced back to you personally. Now we are going first to do a practice round that will not count for money.

Appendix A4.2 Random forest algorithm

We used random forest (RF) algorithm to identify important variables that influence farmers decision to use mineral fertilizer. RF method is a machine learning based on an ensemble of decision trees that do not depend on statistical assumptions (Breiman, 2001). Because of its model-free nature, the goal is predictive power, rather than reporting point estimates and standard errors of a particular parameter (Athey and Imbens, 2019). The popularity of RF stems from the combination of randomizing the data and variables across many trees and providing high prediction accuracy under predictor correlations (Hastie et al., 2008; Genuer et al., 2010). RF method uses a variation of bagging whereby many independent trees are learned from the same training data. The out-of-bag (oob) samples[18], those not used for training a specific tree, can be used as an unbiased measure of performance.

The statistical framework by considering a learning set $L = (X_1, Y_1), ..., (X_n, Y_n)$ made of n independently and identically distributed (i.i.d) observations of a random vector (X, Y) (Genuer et al., 2010). Vector $X = (X^1, ..., X^p)$ contains p predictors (explanatory variables), which include risk preferences and WICI uptake, and Y is farmers' mineral fertilizer use. The principle of RF is to combine many binary decision trees built using several bootstrap samples coming from the learning sample L and choosing randomly at each node a subset of explanatory variables X. Following Hastie et al. (2008), by randomly selecting the explanatory variables, the RF algorithm in equation 4.8 aims to reduce the correlation between the trees (ρ) without increasing the variance (σ^2) too much.

$$\rho\sigma^2 + \frac{1-\rho}{B}\sigma^2 \tag{4.8}$$

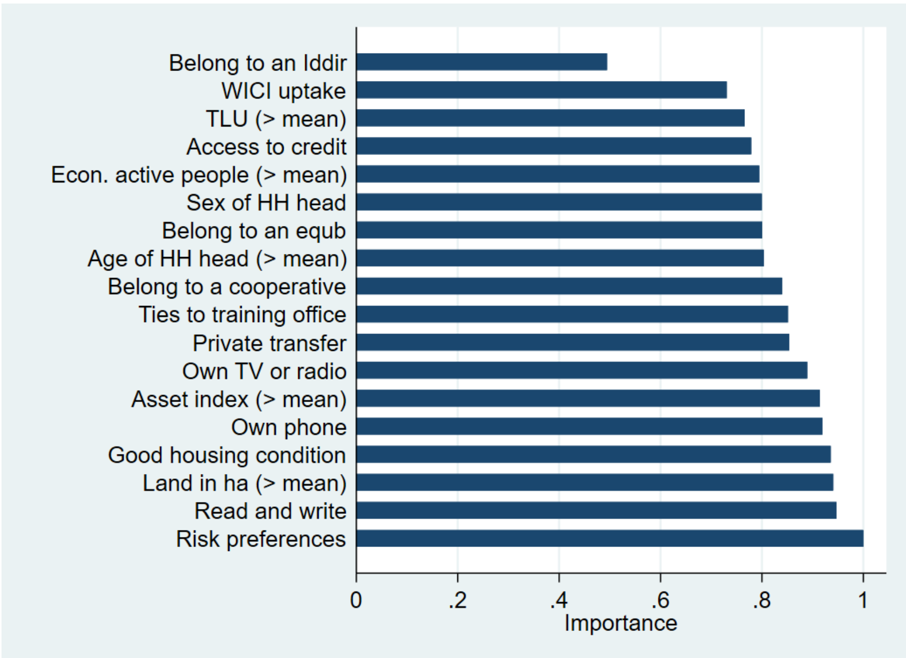
The m explanatory variables are randomly selected as candidates for splitting such that $m \leq p$. As such, reducing m will reduce the correlation between any pair of trees in the ensemble, and hence reduce the variance of the average of B i.d. (identically distributed, but not necessarily independent) random trees. After B such trees are grown, the RF regression to make a prediction at a new point x is:

$$\hat{f}_{rf}^{B}(x) = \frac{1}{B}\sum_{b=1}^{B} T(x; \Theta_b) \tag{4.9}$$

where Θ_b in equation 4.9 characterizes the b^{th} RF tree in terms of split variables, cut-points at each node, and terminal-node values.

After training RF, variable importance (predictive power) is evaluated using the oob sample of data, which are not used for constructing the current tree. Variables with high importance in the figure below are drivers of mineral fertilizer use. By contrast, variables with lower variable importance values have lower predictive power on farmers' decision to use mineral fertilizer.

[18] For each observation $Z_i = (X_i, Y_i)$, oob samples are bootstrap samples in which Zi did not appear (Hastie et al., 2008).



Appendix Figure A4.1: Variable importance plot

Notes: Own computation. All variables are categorical to improve comparability.

Appendix A4.3 Appendix tables

Appendix Table A4.1: Description and statistics of variables

Variables	Description	Obs	Mean	Std.Dev.	Min	Max
Variables of interest						
risk-taker	binary; =1 if risk-taker, 0 otherwise.	239	0.439	0.497	0	1
risk-neutral	binary; =1 if risk-neutral, 0 otherwise.	239	0.172	0.378	0	1
risk-averse	binary; =1 if risk-averse, 0 otherwise.	239	0.389	0.489	0	1
mineral fertilizers use	binary; =1 if the household (HH) uses mineral fertilizers, 0 otherwise.	231	0.346	0.477	0	1
WICI purchase	binary; =1 if buy insurance, 0 otherwise.	239	0.5021	0.501	0	1
insurance foreman	binary; =1 if the HH lives in the same village with the insurance foreman, 0 otherwise.	239	0.548	0.499	0	1
Control variables						
age	continuous variable for the age of the HH head.	239	40.60	10.57	19	72
sex	binary; =1 if the HH head is male, 0 otherwise.	239	0.782	0.413	0	1
education	binary; =1 if the HH head attend formal education, 0 otherwise.	239	0.393	0.490	0	1
active people	continuous variable for the number of economically active HH members.	239	2.724	1.920	1	13
asset holding	continuous variable for asset holding.	239	15.41	12.24	3.898	83.94
tropical livestock unit	continuous variable for the total livestock holding.	239	5.017	4.376	0	19.90
land holding	continuous variable for total land holding.	239	1.216	0.826	0	4.625
housing condition	binary; =1 if the housing condition is average and above, 0 if leaking or falling apart.	239	0.799	0.401	0	1
access to credit	binary; =1 if the HH gets credit, 0 otherwise.	239	0.766	0.424	0	1
private transfer	binary; =1 if the HH received private transfers, 0 otherwise.	239	0.393	0.490	0	1
cooperative member	binary; =1 if the HH is a member of a cooperative organization, 0 otherwise.	239	0.699	0.460	0	1
iddir member	binary; =1 if the HH is a member of a burial savings group, 0 otherwise.	239	0.962	0.191	0	1
equb member	binary; =1 if the HH is a member of an informal rotating saving and credit association, 0 otherwise.	239	0.456	0.499	0	1
ties with training office	binary; =1 if the HH head has personal ties to training officer(s) of R4 project, 0 otherwise.	239	0.372	0.484	0	1
own TV or radio	binary; =1 if the HH owns television or radio, 0 otherwise.	239	0.368	0.483	0	1
own phone	binary; =1 if the HH owns phone, 0 otherwise.	239	0.753	0.432	0	1

Appendix Table A4.2: Falsification tests: Testing the correlation between the instrumental variable and risk-aversion of non-purchasers

Variables	(1) Probit (Risk-aversion)		(2) Probit (Risk-aversion)	
	Coeff.	AME	Coeff.	AME
same village with foreman	0.0910	0.0328	0.2806	0.0900
	(0.2482)	(0.0894)	(0.2762)	(0.0872)
age			-0.0009	-0.0003
			(0.0147)	(0.0047)
sex			-0.1873	-0.0601
			(0.3657)	(0.1171)
education			-0.1541	-0.0494
			(0.2848)	(0.0906)
active people			-0.0475	-0.0152
			(0.0819)	(0.0261)
asset holding			0.0410**	0.0131**
			(0.0181)	(0.0055)
tropical livestock unit			-0.0091	-0.0029
			(0.0347)	(0.0111)
land holding			0.2031	0.0651
			(0.1615)	(0.0510)
housing condition			-0.1133	-0.0363
			(0.3262)	(0.1045)
access to credit			-0.2107	-0.0675
			(0.2902)	(0.0921)
private transfer			-0.1537	-0.0493
			(0.2750)	(0.0882)
cooperative member			-0.0960	-0.0308
			(0.3345)	(0.1071)
iddir member			-0.1170	-0.0375
			(0.6723)	(0.2158)
equb member			-0.3120	-0.1000
			(0.2814)	(0.0896)
ties with training office			0.3124	0.1002
			(0.4813)	(0.1544)
own TV or radio			-1.0334***	-0.3314***
			(0.3631)	(0.1079)
own mobile phone			0.0246	0.0079
			(0.3874)	(0.1243)
Constant	-0.4795***		-0.2147	
	(0.1506)		(0.8292)	
Observations	119	119	119	119

Notes: Robust standard errors in parentheses.

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

AME stands for average marginal effect.

Appendix Table A4.3: Selection effect after adjusting only for the observables

Variables	(1) Probit (WICI uptake)		(2) Probit (WICI uptake)	
	coeff.	AME	Coeff.	AME
risk-averse	0.3240*	0.1277**	0.1779	0.0434
	(0.1676)	(0.0644)	(0.2057)	(0.0498)
age			0.0259**	0.0063**
			(0.0112)	(0.0026)
sex			-0.1888	-0.0460
			(0.2558)	(0.0622)
education			0.1972	0.0481
			(0.2084)	(0.0513)
active people			0.1408**	0.0343**
			(0.0566)	(0.0138)
asset holding			-0.0090	-0.0022
			(0.0098)	(0.0024)
tropical livestock unit			-0.0797***	-0.0194***
			(0.0277)	(0.0064)
land holding			-0.2946**	-0.0718**
			(0.1498)	(0.0364)
housing condition			0.1226	0.0299
			(0.2659)	(0.0649)
access to credit			0.4025*	0.0981*
			(0.2320)	(0.0562)
private transfer			0.0025	0.0006
			(0.2179)	(0.0531)
cooperative member			-0.7394***	-0.1802***
			(0.2464)	(0.0560)
iddir member			0.8545	0.2082
			(0.7648)	(0.1843)
equb member			0.2909	0.0709
			(0.2516)	(0.0604)
ties with training office			1.9702***	0.4800***
			(0.2775)	(0.0381)
own TV or radio			0.3258	0.0794
			(0.2662)	(0.0648)
own mobile phone			-0.1338	-0.0326
			(0.2792)	(0.0679)
Constant	-0.1205		-2.0706**	
	(0.1042)		(0.9393)	
Observations	239	239	239	239

Notes: Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
AME stands for average marginal effect.

Appendix Table A4.4: The effect of WICI on risk-aversion after adjusting only for observable household characteristics

Variables	(1) Ordered Probit (Risk preferences)				(2) Probit (Risk-aversion)	
	Coeff.	AME			Coefficient	AME
		Risk-taking	Risk-neutral	Risk-aversion		
purchase WICI	0.1410	-0.0513	0.0015	0.0498	0.1674	0.0578
	(0.1996)	(0.0723)	(0.0027)	(0.0701)	(0.2237)	(0.0769)
age	0.0083	-0.0030	0.0001	0.0029	0.0015	0.0005
	(0.0081)	(0.0029)	(0.0001)	(0.0028)	(0.0092)	(0.0032)
sex	0.0092	-0.0034	0.0001	0.0033	-0.0819	-0.0283
	(0.2295)	(0.0835)	(0.0025)	(0.0810)	(0.2417)	(0.0835)
education	0.0678	-0.0247	0.0007	0.0239	-0.0834	-0.0288
	(0.1771)	(0.0645)	(0.0021)	(0.0625)	(0.1985)	(0.0685)
active people	0.0804	-0.0293*	0.0009	0.0284*	0.0777	0.0268
	(0.0492)	(0.0177)	(0.0011)	(0.0172)	(0.0526)	(0.0180)
asset holding	0.0054	-0.0020	0.0001	0.0019	0.0093	0.0032
	(0.0090)	(0.0033)	(0.0001)	(0.0032)	(0.0090)	(0.0031)
tropical livestock unit	-0.0247	0.0090	-0.0003	-0.0087	-0.0093	-0.0032
	(0.0247)	(0.0089)	(0.0004)	(0.0086)	(0.0262)	(0.0090)
land holding	0.1681	-0.0612	0.0018	0.0593	0.2124	0.0734
	(0.1047)	(0.0379)	(0.0022)	(0.0367)	(0.1312)	(0.0446)
housing condition	-0.1111	0.0404	-0.0012	-0.0392	-0.1079	-0.0373
	(0.2142)	(0.0778)	(0.0026)	(0.0755)	(0.2376)	(0.0820)
access to credit	-0.5547***	0.2019***	-0.0060	-0.1958***	-0.4882**	-0.1687**
	(0.1927)	(0.0674)	(0.0067)	(0.0651)	(0.2187)	(0.0733)
private transfer	0.0428	-0.0156	0.0005	0.0151	0.1308	0.0452
	(0.1686)	(0.0613)	(0.0019)	(0.0595)	(0.1864)	(0.0642)
cooperative member	0.1693	-0.0616	0.0018	0.0598	0.0902	0.0312
	(0.2055)	(0.0745)	(0.0030)	(0.0721)	(0.2230)	(0.0769)
iddir member	0.0090	-0.0033	0.0001	0.0032	-0.2542	-0.0878
	(0.5103)	(0.1857)	(0.0056)	(0.1801)	(0.4878)	(0.1685)
equb member	-0.2848	0.1036	-0.0031	-0.1006	-0.3995*	-0.1380**
	(0.1847)	(0.0666)	(0.0037)	(0.0648)	(0.2056)	(0.0697)
ties with training office	0.3620*	-0.1317*	0.0039	0.1278*	0.5560**	0.1921**
	(0.2179)	(0.0782)	(0.0045)	(0.0762)	(0.2364)	(0.0798)
own TV or radio	-0.2658	0.0967	-0.0029	-0.0938	-0.4667**	-0.1613**
	(0.2083)	(0.0750)	(0.0036)	(0.0731)	(0.2340)	(0.0794)
own mobile phone	0.0164	-0.0060	0.0002	0.0058	-0.0105	-0.0036
	(0.2293)	(0.0834)	(0.0025)	(0.0809)	(0.2428)	(0.0839)
Constant					-0.1791	
					(0.6485)	
Observations	239				239	

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

AME stands for average marginal effect.

See section 4.3.2 for the explanations on the dependent variables in columns 1 and 2.

Appendix Table A4.5: Coefficient estimates of the ESP model for adoption of mineral fertilizers

Variables	(1) Probit (WICI uptake) Selection model	(2) Probit (Mineral Fertilizer Use) Purchasers	Non-purchasers
same village with foreman	0.7501***		
	(0.1734)		
age	0.0264**	0.0246*	0.0199
	(0.0123)	(0.0127)	(0.0140)
sex	-0.1250	0.5713	-0.2801
	(0.2655)	(0.3905)	(0.3234)
education	0.0437	0.2232	0.4925**
	(0.1880)	(0.2386)	(0.2339)
active people	0.1401**	0.0567	-0.0051
	(0.0566)	(0.0666)	(0.0782)
asset holding	-0.0046	0.0190	-0.0337**
	(0.0127)	(0.0129)	(0.0166)
tropical livestock unit	-0.0878***	-0.0477	0.0315
	(0.0256)	(0.0350)	(0.0320)
land holding	-0.3051*	-0.1350	-0.4658***
	(0.1561)	(0.2100)	(0.1710)
housing condition	0.1164	0.3357	-0.2610
	(0.2536)	(0.3905)	(0.2989)
access to credit	0.4263*	0.2748	0.1231
	(0.2398)	(0.3561)	(0.2756)
private transfer	0.1014	-0.7282**	0.3609
	(0.2147)	(0.2898)	(0.2537)
cooperative member	-0.7316***	-0.4266	-0.4866*
	(0.2337)	(0.2638)	(0.2586)
iddir member	1.0368	0.1512	1.5145**
	(0.7269)	(0.6144)	(0.7086)
equb member	0.1178	0.0220	-0.1046
	(0.2246)	(0.2932)	(0.2476)
ties with training office	1.9954***	1.0420***	1.4253***
	(0.2732)	(0.3007)	(0.4404)
own TV or radio	0.2022	-0.3141	1.0087***
	(0.2943)	(0.3292)	(0.3532)
own mobile phone	-0.0612	0.3666	0.1513
	(0.2864)	(0.3550)	(0.3480)
Constant	-2.6298***	-3.3458***	-1.3837
	(0.9115)	(0.9944)	(0.8937)
rho (ρ_i)		1***	1***
		(4.32e-13)	(1.09e-11)
Observations	231	231	231
Test of ρ_1=ρ_0=0 (p value)		0.0071	

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. ESP stands for endogenous switching probit.We used Stata commands developed by Lokshin and Sajaia (2011) for the ESP analysis.

Appendix Table A4.6: Adoption of mineral fertilizers conditioning on observable factors

Variables	(1) Probit (Mineral Fertilizer Use)		(2) Probit (Mineral Fertilizer Use)	
	Coeff.	AME	Coeff.	AME
purchase WICI	-0.0244	-0.0090	-0.3665	-0.1224
	(0.1701)	(0.0627)	(0.2358)	(0.0778)
age			0.0091	0.0030
			(0.0098)	(0.0033)
sex			0.3179	0.1062
			(0.2553)	(0.0844)
education			0.3151	0.1053
			(0.1988)	(0.0654)
active people			-0.0247	-0.0083
			(0.0518)	(0.0173)
asset holding			0.0027	0.0009
			(0.0085)	(0.0028)
tropical livestock unit			0.0145	0.0048
			(0.0250)	(0.0083)
land holding			-0.3298**	-0.1102**
			(0.1394)	(0.0456)
housing condition			-0.0799	-0.0267
			(0.2496)	(0.0833)
access to credit			0.3387	0.1132
			(0.2328)	(0.0773)
private transfer			-0.1191	-0.0398
			(0.1918)	(0.0639)
cooperative member			-0.0541	-0.0181
			(0.2181)	(0.0728)
iddir member			0.6029	0.2014
			(0.4964)	(0.1649)
equb member			-0.2113	-0.0706
			(0.2147)	(0.0715)
ties with training office			0.3413	0.1140
			(0.2431)	(0.0806)
own TV or radio			0.2160	0.0722
			(0.2336)	(0.0776)
own mobile phone			0.2664	0.0890
			(0.2609)	(0.0870)
Constant	-0.3830***		-1.6433**	
	(0.1208)		(0.6428)	
Observations	231	231	231	231

Notes: Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
AME stands for average marginal effect.

CHAPTER 5

CONCLUSION

5.1 Main Findings

Climate change is a reality in SSA where rainfed agriculture is the dominant livelihood activity for the majority of the population. The vagaries of weather and climate make rural households in the region vulnerable to poverty. In particular, children in SSA are the most vulnerable household members to the worst consequences of climate shocks on their immediate and future welfare indicators. Enhancing the climate resilience of rural households has received a lot of attention among researchers and practitioners as a way forward to improve ex-ante and ex-post climate risk management capacities and reduce vulnerabilities. Hence, achieving climate resilience requires the households' capacity to take coping actions that increase their ability to buffer the welfare effects of climate shocks in the post-shock period. It also requires households' decisions to uptake strategies that enable them to adapt to and mitigate the negative consequences of climate shocks. What remains for researchers and development practitioners is to adequately incorporate the concept of climate resilience in the design of policy and programme interventions aiming to alleviate poverty and spur economic development in SSA. This dissertation investigates rural household decisions and behavioural responses to facilitate evidence-informed policy-making that intends to enhance the households' capacity to adequately manage climate shocks without sacrificing their investments on human, physical and natural capital. To this end, we examine rural households' decision-making under climate risk using three separate empirical studies.

In the aftermath of climate shocks, households may lack the capacity to take coping measures that improve or maintain the immediate and longer-term welfare indicators of their members. Chapter 2 examines the gender differential impacts of drought on rural households' human capital formation, child health and schooling, and explores the pathways for these impacts. The chapter contributes to the literature on the welfare impacts of climate shocks on children by providing detailed analyses on the contemporaneous link between child health and schooling, and households' gender-based coping responses that may introduce heterogeneity in the direct and indirect effects of climate shocks on child human capital. We link the Ethiopia Rural Socioeconomic Survey (ERSS) panel data with climate data to run a within-child variation estimations. Consistent with the findings of Alderman et al. (2006), Hoddinott (2006), Thai and Falaris (2014), Zamand and Hyder (2016), Duque et al. (2018), and Nguyen and Minh Pham (2018), we find that drought has a negative impact on child health and education. We also provide a novel empirical evidence on the detrimental impact that drought-induced child illness has on schooling outcomes. As such, the negative impact of drought on a child's highest grade completed is significantly mediated, albeit not entirely, through ill health. The direct and indirect (mediated) effects of drought on child schooling are disproportionately concentrated among girls. Further analysis to unpack the mechanisms for this reveals that gender bias in the intrahousehold resource allocation to seek medical treatment for their ill female children plausibly explains how poor health conditions linger and obstruct schooling of girls. Moreover, similar to the findings of Björkman-nyqvist (2013), demand for female child labour for non-agricultural activities is another mechanism that may explain why the direct effect of drought on child schooling is robust only for girls. As such, households sacrifice human capital formation of their female children as a coping measure when the available resources are limited during drought seasons.

As climate shocks are becoming more frequent, households need to switch from conventional to sustainable farming practices to adequately mange climate risks (Di Falco and Veronesi, 2013; Carter and Janzen, 2015). There are climate-smart agricultural innovations with triple wins of increasing the households' income, enhancing their capacity to adapt to the effects of climate risks, and providing a solution to the climate change challenge. However, the uptake of climate-smart practices by rural households in SSA remains low (Garrity et al., 2010; Glover et al., 2012). A market-based policy instrument known as PES can play a role in inducing a change in behaviour among rural households in favour of adopting climate-smart agricultural practices, and thus may serve as part of the overall climate change adaptation and mitigation strategy. In Chapter 3, we conducted a discrete choice experiment with rural households in Ethiopia to elicit rural households' willingness to accept incentives under a PES scheme for adopting climate-smart agroforestry – an agricultural innovation that have climate change adaptation and mitigation benefits. The results show that households derive higher utility from receiving up-front payments for ecosystem services. Moreover, households prefer a PES program that uses food (wheat) as payment, requires a low number of planted trees, and has a shorter contract period. The study reveals the presence of individual- and class-specific heterogeneous preferences on the design features of the PES scheme. These findings shed light on the considerations that must be accounted for when designing and implementing PES schemes that promote large-scale adoption of climate-smart agroforestry, which would transform rainfed agriculture in SSA into a sustainable farming system. The chapter contributes to the PES literature on integrating efficiency and equity concerns in a PES scheme by proposing a novel design feature that accommodates climate-smart agricultural innovations and a payment arrangement that is suitable for poor rural households.

The last empirical work, Chapter 4, examines the effect of weather index-based crop insurance (WICI) – a formal climate risk transfer mechanism – on farmers' risk preferences. Rural households' exposure to uninsured climate risks triggers what Rosenzweig and Binswanger (1993) call farmers' need for "self-insurance", which may lead to formation of risk-averse attitudes. In this respect, households' ex-ante response to climate shocks may involve avoiding high-risk but profitable agricultural technologies and investments so that they can minimize the associated income variability. In the long-term, risk-aversion ultimately traps rural households in persistent poverty (Carter and Barrett, 2006; Yesuf and Bluffstone, 2009; Dercon and Christiaensen, 2011). Chapter 4 provides novel empirical evidence on the impact of WICI market on risk preferences and contributes to the literature that explores the possible causes of change in individual risk attitude, a major driver of agricultural technology adoption. We collected survey and lab-in-the-field experimental data from rural households that have access to WICI in Ethiopia. WICI uptake significantly reduces risk-aversion of farmers and ultimately increases real-life risk-taking behaviour in their agricultural investment decisions as exemplified by mineral fertilizer use. Therefore, WICI uptake changes farmers risk preferences by plausibly modifying how farmers interpret the operating environment for farming.

To sum up, this dissertation provides micro-level evidence on the effects of climate shocks and climate risk management policies and strategies on rural household decisions and behavioural responses that determine their immediate and long-term income-generating capacities. Rural households' behavioural responses and decisions are at the centre of our analyses to better understand the impact pathways in the climate risk–welfare nexus and identify policy-related drivers for adoption of climate-smart agricultural innovations and high-risk but profitable agricultural technologies. By doing so, this dissertation provides empirical evidence that can inform the design of social protection programmes, incentive-based environmental policies, and formal climate risk transfer mechanisms that can bring desirable welfare effects (such as increasing household income and human capital development) in the face of climate change in SSA.

5.2 Research Limitations and Areas for Future Research

This dissertation has a number of limitations that future studies may address in order to validate the generalizability of the findings in the three empirical chapters.

In establishing a contemporaneous causal relationship between child health and schooling, Chapter 2 relies on within-child variation estimators to account for the effects of unobserved time-invariant heterogeneities at the child, household and higher-cluster (e.g. community) levels. We also use recursive bivariate estimation with exclusion restriction to correct for biases associated with the endogeneity of child health due to time-varying heterogeneities. Despite these efforts, we cannot be completely sure that we exogenously varied health status to identify its causal mediation effect on child education in the absence of data obtained from field experiments. The chapter also relies only on self-reported child health and schooling outcome variables, which may introduce measurement errors due to recall bias. However, we argue that health and education are salient individual characteristics which are less susceptible to recall bias in the short-term. Existing research also shows that self-reported measures of health status and education have the greatest degree of reliability and construct validity (Sticca et al., 2017; Vaillant and Wolff, 2012), and are appropriate regardless of gender of respondents (Kuhn et al., 2006). Therefore, our estimates are less likely to be biased due to using self-reported child health and schooling outcome variables. Future studies using different data sets that allow natural experiments and objective measures of child human capital (i.e laboratory tests and screens, school attendance sheets, test scores) would verify the validity of our identification strategy and findings. Moreover, while gender bias is a major pathway for the impact of climate shocks on child human capital, due to lack of data, our study cannot identify why it exists. Future observational and experimental studies in this direction will also give behavioural and economic explanations to the root cause of gender bias in the context of SSA.

In an effort to identify the design features of a PES scheme that can induce rural households' willingness to adopt climate-smart agricultural innovations, Chapter 3 conducts a stated preference survey to elicit farmers' preferences to adopt climate-smart agroforestry in response to a hypothetical PES program that rewards planting fertilizer trees on their agricultural land. It has been well recognized that responses to hypothetical questions may deviate systematically from responses observed in real world interactions. As such, data collected in no-incentive environments may fail to achieve the goal of accurately representing real world behaviour. This deviation, hypothetical and strategic bias, is a common challenge in stated preference studies. Despite the fact that we use DCE, which is suggested to be a more appropriate approach to minimize such biases than other stated preference methods, we cannot rule out the possibility that hypothetical and social desirability biases may affect our findings. Future field experiments based on the design features of our DCE study will show the applicability and practicality of our findings in terms of getting rural households adopt climate-smart agroforestry.

In Chapter 4, we use a cross sectional incentive-compatible risk experiments to measure individual risk preferences at one point in time. However, measuring risk preference parameters of a given individual over time would be more informative as one can compute the within-farmer effects of WICI uptake on risk-aversion. Further investigation on the impact of crop insurance on risk-aversion of farmers using experimental panel data would verify the generalizability of our findings in a dynamic setting.

In a broader view, although Ethiopia can adequately represent the prevailing situation in SSA in terms of livelihood strategies and challenges, cross-national comparative assessments would have painted a broader picture of household-level climate resilience in the region. In light of this, future similar research in other SSA countries would enable cross country comparisons to facilitate policy learning by deriving lessons from various country experiences. Moreover, this dissertation provides only micro-level empirical evidence taking households and children as a unit of analysis. However, it is equally important to conduct meso- and macro-level analyses to examine the capacity of communities and nations to withstand the impacts of climate shocks and adequately prepare to minimize their future vulnerabilities to shock-induced poverty and inequality. Such endeavour may require a single measure of climate resilience to facilitate ranking and profiling communities and countries. Future studies in this direction would benefit a lot from micro-level studies, like the works in this dissertation, for the selection of dimensions and identifying indicators by focusing on theory-based and empirically verified measures of coping and adaptive capacity.

5.3 Policy Recommendations

The findings of the dissertation are relevant for policy interventions that intend to enhance the ability of households to adequately respond to climate shocks in the pre- and post-shock periods. Chapter 2 presents evidence for the impact of drought on human capital. The direct and mediated effects of drought on schooling outcomes are disproportionately large for female children. The study shows that ill health is a significant mediating factor through which drought affects a female child's education. The policy lesson that emerges from this finding is that demand and supply side interventions should be gender-equitable to fill the observed gender gap in schooling resulted from gender biases in intra-household resource allocation for health care and demand for child labour in the face of climate shocks. As such, policy interventions that intend to increase households' income to improve their spending on health care and reduce the opportunity cost of child labour may mitigate the negative impact of climate shocks on human capital of female children. In the supply side, allowing free health care at public health facilities or school health programmes that target child health of girls can pay "double dividend" by improving both their health and education simultaneously.

Incentive-based environmental policies can induce large-scale adoption of agricultural innovations that not only play a significant role in enhancing the households' capacity to adapt to climate change but also put them at the centre of the solution to the climate change challenge. Chapter 3 provides policy-relevant information on the considerations that must be taken into account for designing and implementing PES schemes that promote adoption of climate-smart agroforestry among farmers in SSA and particularly in Ethiopia. The concept of conditional cash transfers can be merged with PES to come up with a novel environmental policy instrument that simultaneously addresses the equity and efficiency concerns. Up-front payments starting from the initial year would enable the households to bear the short-term income and consumption losses related to their investment decision. Successful implementation of the proposed environmental policy requires developing strategies to increase outreach beyond the average farmer to induce large-scale uptake of climate-smart agricultural innovations in the landscapes of SSA. Moreover, the lack of agricultural extension system's effect on household decision to uptake climate-smart agroforestry may suggest the need for innovative solutions to improve household's access to information on sustainable agricultural practices. One solution can be through national or local mass-media programs specifically designed to promote climate-smart agroforestry.

The findings of Chapter 4 have important implications for policy and programme interventions that intend to spur economic development in agrarian economies where the effects of climate shocks are highly felt. In the presence of formal climate risk transfer mechanisms, rural households' WICI uptake significantly reduces their risk-aversion. Individual risk-aversion is linked to economic development by influencing households' investment decisions on high-risk high-return agricultural technologies that, in turn, determine their income. The role of climate risk management policies in general and WICI in particular in the poverty alleviation and economic development can also be channelled through their effects on individual risk-aversion. Hence, risk management policies and strategies can have long-term effects on rural households by bringing about desirable economic behaviour that may enable them break out of poverty traps and enjoy virtuous cycle of increasing income. Therefore, policies that intend to increase the adoption of risky but profitable agricultural technologies in SSA should work in tandem with climate risk management strategies to improve the uptake of the technologies by safeguarding economic circumstances of households.

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VALORIZATION ADDENDUM

The addendum on the valorization of this doctoral dissertation is added in compliance with article 23.5 of the "Regulation governing the attainment of doctoral degrees at Maastricht University" decreed by resolution of the board of deans, dated 3 July 2013.

The outputs of this dissertation assist informed policy making to facilitate the realisation of the Sustainable Development Goals (SDGs) of the United Nations at individual, household and societal or national levels. At individual-level, the main findings of Chapter 2 show that climate shocks deter human capital formation of children. The impact of climate shocks, particularly drought, on child schooling is mediated through child illness. The most significant mechanism is households' lack of financial capacity to pay for the medical treatment of their ill children during drought seasons. In the incidence of illness, female children are in a disadvantaged position since parents seem to disfavour them when it comes to allocating resources for medical treatment. Moreover, households employ female children's labour for non-farm activities during shock periods. Consequently, the schooling outcomes of female children are more likely to be negatively affected by climate shocks. The findings of Chapter 2 imply for policy actions to achieve goals 3, 4, and 5 of the SDGs. In the context of drought prone SSA countries, the effectiveness of policy and programme interventions that attempt to close the gender gap in schooling can be enhanced if due considerations are given to improving health and reducing labour use of female children.

Chapter 3 and Chapter 4 take the household as the unit of analysis and attempt to address research questions that are in line with the targets under SDG 1, 2 and 13. In Chapter 3, the main focus is identifying the design features of an environmental policy to induce climate actions at household level to enhance their climate resilience through facilitating their capacity to adapt to and mitigate the effects of climate shocks. The chapter presents empirical evidence on how incentive-based policy choices can affect climate actions on private lands as demonstrated by agricultural households' willingness to plant trees on their farm plots. Incentives are justified considering the liquidity constraints rural households face coupled with the time lag to realise the financial and environmental benefits of their investments in climate actions. In this respect, desirable land use decisions improve the households' income and food production, and simultaneously provide environmental benefits such as reducing agricultural greenhouse gas emissions, carbon sequestration and improving the microclimate. As such, with the right policy, agricultural lands in SSA have the potential to render the triple benefits of food production, biodiversity conservation and carbon sequestration.

Chapter 4 reveals that agricultural households' access to formal climate risk transfer institutions change the way they perceive the world and thus induce a shift in their risk preferences towards less risk-averse attitudes. Ultimately, households are able to adopt high-risk high-return agricultural technologies that may enable them enjoy virtuous cycle of increasing income. Hence, policy efforts that enable rural households in SSA manage climate risks can bring out desirable economic behaviour that accelerates the process of dragging poor and vulnerable people out of poverty traps.

The findings of all the chapters of the dissertation have also implications for societal and national level poverty eradication and economic development efforts. Educating female children can lay the foundation for creating a society with empowered women who have equal access to resources and opportunities to lead the kind of life they value. Hence, based on the second chapter, human capital investments in female children can have longer-term aggregate desirable effects on nutrition, education, health and managing population growth. The third empirical chapter explores the policy options to transform conventional land-intensive agricultural activities, which support most SSA economies, into a sustainable agriculture with higher productivity and positive environmental spillovers. This transition not only reduces rural households' susceptibility to the effects of climate shocks but also puts them at the centre of the solution to the climate change challenge. Projecting the relevance of the findings of the fourth chapter beyond the household level, economic behaviours of households can also determine accumulation of human, physical and financial capital at meso and macro levels. Societies comprising households that are characterised by risk taking may attain low productivity gaps and income inequalities.

Chapter 3 and Chapter 4 are presented in the UNU-MERIT annual internal conference series. With the aim of reaching scientific community, policy makers and practitioners outside the UNU-MERIT, all chapters of the dissertation were presented in international conferences such as: the agricultural greenhouse gas emission and food security - connecting research, policy and practice in Berlin; the World Banks's land and poverty conference in Washington D.C.; the 4th agroforestry congress in Montpellier; and Venice summer school conference on poverty, inequality and their associations with disaster and climate change in Venice. Furthermore, Chapter 2 is published as UNU-MERIT working paper #2019-052. Chapter 3 and Chapter 4 have been published in reputable peer-reviewed journals. Chapter 3 is published as "Haile, K.K., Tirivayi, N., and Tesfaye, W. (2019). Farmers' willingness to accept payments for ecosystem services: The case of climate-smart agroforestry in Ethiopia. *Ecosystem Services*, 39: 100964", and Chapter 4 as "Haile, K.K., Nillesen, E., and Tirivayi, N. (2020). Impact of formal climate risk transfer mechanisms on risk-aversion: Empirical evidence from rural Ethiopia. *World Development*, 130: 104930".

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The author was born in May 1984 in Addis Ababa, Ethiopia. He obtained his B.Sc. degree in Agribusiness Management in 2006 and M.Sc. degree in Agricultural Economics in 2011 both from Haramaya University, Ethiopia. He served the same University as a lecturer and an academic researcher before he joined UNU-MERIT and its school of governance at Maastricht University in September 2015 to pursue his Ph.D. studies in Economics and Governance. He obtained a scholarship from NWO-Nuffic Netherlands Fellowship Programme (NFP) to finance his Ph.D. studies. This gave him the opportunity to design and carryout his own research work in Ethiopia. His fields of research interest and expertise include impact evaluation, climate resilience, lab and field experiments, environmental economics, food and nutrition security, human capital development, and poverty and inequality dynamics.