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Dissertation

# Climate Variability, Social Capital and Food Security in Sub-Saharan Africa: Household Level Assessment of Potential Impacts and Adaptation Options.

Submitted by:

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#### Summary

Climate variability and poor distribution of rainfall often causes serious agricultural production losses and worsens food insecurity. Given that the direct effects of climate change and variability are transmitted through the agricultural sector, improving farm households' capacities to adapt to the adverse effects of climate-related shocks is an important policy concern. This thesis applied a stochastic Agent-based Model (ABM) that is capable of simulating the effects of different adaptation options by capturing the dynamic changes of climate and prices, as well as the dynamic adaptive process of different farm households to the impacts of these changes. The agent-based simulations conducted in this thesis address the special challenges of climate and price variability in the context of small-scale and subsistence agriculture by capturing non-separable production and consumption decisions, as well as the role of livestock for consumption smoothing. To ensure the reliability and usefulness of results, the model was validated with reference to land-use and overall poverty levels based on observed survey values.

In particular, the study used disaggregated socio-economic, price, climate and crop yield data to quantify the impacts of climate and price variability on food security and poverty at the household level. Furthermore, the study explicitly captured crop-livestock interactions and the "recursive" nature of livestock keeping when examining the effects of climate and price variability. The thesis additionally examined how specific adaptation strategies and policy interventions, especially those related to the promotion of credit, improved seed varieties, fertilizer subsidy and off-farm employment, affect the distribution of household food security and poverty, the study further considered indirect impacts through changes in the price of agricultural inputs and livestock holding.

In terms of coping strategies, the simulation results in this thesis show that the effects of climate and price variability on consumption are considerable, but smaller for those households with relatively large livestock endowments. In addition, the study also found that farm households with a large plantation area of eucalyptus were able to cope with the effects of variability. Therefore, our results suggest that self-coping strategies are important but not sufficient and should be complemented with

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appropriate policy interventions. In terms of policy interventions, the study found that policy intervention through the expansion of credit and fertilizer subsidy along with innovation through the promotion of new crop varieties that are resilient and adapted to local conditions are the most effective adaptation options for the case of Ethiopia. In addition, the simulation results underscore that adaptation strategies composed of a portfolio of actions (such as credit and fertilizer subsidy along with new technologies) are more effective compared to a single policy intervention. For Ghana, the study suggests that if expansion of production credit is complimented by irrigation, it can provide a way to achieve food security under climate and price variability.

In order to design a best-fit intervention instead of a 'one size fits all' approach, it is important to capture the distribution of effects across locations as well as households. The great strength of this study is its agent-based nature, which enables exploration of how effects are distributed across farm households. The simulation results clearly show that poor farms are vulnerable to climate and price variability, under which they suffer food insecurity, while a small group of wealthy farms are better off due to higher prices achieved when selling crops. The result from this thesis further underscores the need for improving adaptive capacity, as a large proportion of farm households are unable to shield themselves against the impacts of price and climate variability.

In what follows, the study further applied standard micro-econometric techniques to examine the role of social capital and informal social networks on consumption insurance and adoption of risk mitigating land management practices. In particular, the thesis provides evidence of the effects of different dimensions of social capital on the adoption of soil and water conservation practices across households holding different levels of risk-aversion. The results of the study underscore that social capital plays a significant role in enhancing the adoption of improved farmland management practices and suggests that the effect of social capital across households with heterogeneous risk taking behaviour is different. Finally, by combining household panel data, weather data, self-reported health shocks and detailed social capital information, the last section is able to analyze how social capital buffers some of the implications of weather shocks. In particular, based on the undertaken econometric analyses, the results suggest that households are unable to protect themselves from rainfall shocks. However, households with better social capital are more able to smooth consumption. The study then concludes that in the absence of formal financial and insurance markets, a household's ability to insure consumption against shocks is largely determined by difference in social capital levels.

### Zussammenfassung

Klimavariabilität und ungünstige Verteilung von Regenfällen verursachen oft erhebliche Verluste in der landwirtschaftlichen Produktion, und verschlechtern die Nahrungssicherheit. Da die direkten Auswirkungen des Klimawandels und der Klimavariabilität über den landwirtschaftlichen Sektor übertragen werden, hat die Verbesserung der Möglichkeiten für landwirtschaftliche Haushalte sich an widrige, durch das Klima verursachte Schocks anzupassen, wichtige politische Bedeutung. Die vorliegende Dissertation nutzte ein stochastisches, agentenbasiertes Model, welches in der Lage ist, die Effekte verschiedener Anpassungsoptionen zu simulieren, indem es die dynamischen Entwicklungen von Klima und Preisen, sowie die dynamischen Anpassungsprozesse der verschiedenen landwirtschaftlichen Betriebe an die Auswirkungen dieser Veränderungen erfasst. Die in der vorliegenden Arbeit durchgeführten agentenbasierten Simulationen widmen sich der besonderen Herausforderung der Klima- und Preisänderungen im Kontext der kleinbäuerlichen Selbstversorgungslandwirtschaft, in dem sie die nicht voneinander trennbaren Produktions- und Konsumentscheidungen, sowie die Rolle des Viehbestandes für den Konsumausgleich berücksichtigen. Um die Verlässlichkeit und die Brauchbarkeit der Ergebnisse sicher zu stellen wurde das Modell in Bezug auf Nahrungssicherheit, Landnutzung und allgemeine Armutsgrenze, basierend auf beobachteten Erhebungsdaten, validiert.

Im Besonderen wurden für die vorliegende Studie disaggregierte sozioökonomische Daten, sowie disaggregierte Daten zu Preisen, Klima und Ernteerträgen genutzt, um die Auswirkungen von Klima- und Preisänderungen auf Nahrungssicherheit und Armut auf Haushaltsniveau zu quantifizieren. Des Weiteren wurden Interaktionen zwischen Pflanzenbau und Tierzucht, sowie der "rekursive" Charakter der Viehhaltung bei der Untersuchung der Effekte durch Klima- und Preisänderungen explizit berücksichtigt. Die Dissertation betrachtet darüber hinaus, wie sich bestimmte Strategien und Politikeingriffe, insbesondere diejenigen mit Bezug auf die Förderung von Krediten, verbessertes Saatgut, Düngemittelsubvention und außerbetriebliche Beschäftigung auf die Verteilung von Haushalts-Nahrungssicherheit und Armut im Ergebnis auswirken. Darüberhinaus erfasst die Studie auch die indirekten Auswirkungen durch Änderungen der Preise für landwirtschaftliche Betriebsmittel und Tierhaltung. Was die Anpassungsstrategien betrifft, zeigen die Simulationsergebnisse dieser Dissertation, dass die Auswirkungen von Klima- und Preisvariabilität auf den Konsum zwar beträchtlich sind, jedoch für diejenigen Haushalte mit relativ großem Viehbestand kleiner sind. Außerdem fand die Studie heraus, dass landwirtschaftliche Haushalte mit ausgedehnten Flächen von Eukalyptuspflanzungen in der Lage waren mit den Effekten der Variabilität zurecht zu kommen. Demzufolge legen unsere Ergebnisse nahe, dass Eigenanpassungsstrategien zwar wichtig, jedoch nicht ausreichend sind, und deshalb mit geeigneten Politikinterventionen ergänzt werden sollten. Was die Politikinterventionen betrifft, so fand die Untersuchung heraus, dass im Falle Äthiopiens die Anpassung mittels Innovation durch die Förderung von neuen Feldfruchtsorten, die widerstandsfähig und an die lokalen Verhältnisse angepasst sind, die effektivste Anpassungsmöglichkeit darstellt; gefolgt von der Erweiterung der Kreditund Düngemittelsubventionen. Außerdem unterstreichen die Simulationsergebnisse, dass Anpassungsstrategien bestehend aus einem Bündel von Aktionen (wie z.B. Kredit- und Düngemittelsubventionen zusammen mit neuen Technologien), wirkungsvoller sind als einzelne Politikinterventionen. Im Falle Ghanas legt die Studie nahe, dass eine Kombination von Kreditförderung und Bewässerung ein Weg sein kann, Nahrungssicherung trotz Klima- und Preisvariabilität zu erreichen.

Um eine "Best-Fit-Intervention" entwerfen zu können, anstatt einen Einheitsansatz für alle zu verfolgen, ist es wichtig die Streuung der Effekte über alle Orte (Siedlungen) und Haushalte zu erfassen. Die große Stärke dieser Studie ist ihre agentenbasierte Herangehensweise, die dazu befähigt, zu erforschen, wie die Auswirkungen über die landwirtschaftlichen Haushalte verteilt sind. Die Simulationsergebnisse zeigen deutlich, dass arme Betriebe gegenüber Klima- und Preisvariabilität ungeschützt sind, wodurch sie unter Nahrungsunsicherheit leiden, während eine kleine Gruppe wohlhabender Betriebe durch die höheren Preise für Feldfrüchte finanziell besser gestellt sind. Das Ergebnis der vorliegenden Arbeit unterstreicht weiterhin die Notwendigkeit die Adaptationsfähigkeit zu verbessern, da ein großer Teil der landwirtschaftlichen Haushalte nicht in der Lage sind sich selbstständig gegen die Auswirkungen der Klima- und Preisvariabilität zu schützen. Zusätzlich wurden in der Studie Standardtechniken der Mikroökonometrie angewandt, um die Rolle von Sozialkapital und informellen sozialen Netzwerken auf die Konsumsicherung und die Übernahme von Landmanagementpraktiken zur Risikominderung zu untersuchen. Insbesondere liefert die Dissertation den Beleg für die unterschiedlichen Effekte der verschiedenen Dimensionen von Sozialkapital auf die Übernahme von Wasser- und Bodenschutzmaßnahmen über die verschiedenen Haushalte, mit ihren verschiedenen Risikoaversionsniveaus. Die Ergebnisse der Arbeit heben die wesentliche Rolle der Sozialfonds bei der Erleichterung der Übernahme verbesserter Anbaumethoden hervor, und deuten darauf hin, dass sich die Wirkungen zwischen den einzelnen Haushalten des Sozialkapitals mit heterogener Risikobereitschaft unterscheiden. Schlussendlich, indem Haushaltspaneldaten, Wetterdaten, selbst erhobene Daten über Krankheitsschocks und detaillierte Informationen über Sozialfonds kombiniert wurden, ist es in dem letzten Teil der Arbeit möglich zu analysieren wie Sozialkapital einige der durch Wetterschocks verursachten Folgen abfedern. Insbesondere, basierend auf den durchgeführten ökonometrischen Analysen, zeigen die Ergebnisse, dass sich die Haushalte nicht selbstständig gegen Schocks durch Regenfälle schützen können. Allerdings sind Haushalte mit höherem Sozialkapital eher in der Lage den Konsum konstant zu halten. Die Forschungsarbeit folgert, dass bei Abwesenheit von formalen Finanz- und Versicherungsmärkten die Fähigkeit eines Haushalts seinen Konsum gegenüber Schocks abzusichern größtenteils von den unterschiedlichen Niveaus der Sozialkapital bestimmt wird.

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# List of acronyms

AAU	Addis Ababa University
ABM	Agent Based Model
AIDS	Almost Ideal Demand System
CGIAR	Consultative Group on International Agricultural Research
CIMMYT	International Maize and Wheat Improvement Center
CIMP	Coupled Model Intercomparison Project Phase
CPWF	Challenge Program on Water and Food
CSA	Central Statistical Authority
CSAE	Centre for the Study of African Economies
CPRA	Constant Partial Risk Aversion
DAAD	Deutsche Akademischer Austausch Dienst
DSSAT	Decision Support System for Agrotechnology Transfer
ERHS	Ethiopian Rural Household Survey
ESRC	Economic and Social Research Council
FAO	Food and Agriculture Organization
FAOSTAT	Food and Agriculture Organization Corporate Statistical Database
GLSS	Ghana Living Standard Survey
GSS	Ghana Statistical Service
GTP	Growth and Transformation Plan
IFPRI	International Food Policy Research Institute
IPCC	Intergovernmental Panel on Climate Change
MILP	Mixed Integer Linear Programming
MoFed	Ministry of Finance and Economic Development
MPMAS	Mathematical Programming-based Multi-Agent Systems
NBS	Nile Basin Survey
NMA	National Metrological Agency
ODD	Overview Design and Details
PA	Peasant Association
RCP	Representative Concentration Pathways
SAI	Standardized Anomaly Index
SIDA	Swedish International Development Agency
SIMLESA	Intensification of Maize-Legume Systems for Food Security in Eastern and Southern Africa

SSA	Sub-Saharan Africa
UER	Upper East Region
USAID	United States Agency for International Development

## **Chapter One**

#### 1 Introduction

This introduction presents general information on the impacts of climate and price variability in the context of smallholder farmers in Ethiopia and Ghana. Following this basic introduction, the chapter then opens with a basic conceptual framework on the link between variability and food security and an introduction to the roles possible adaptation options may play. Following the conceptual framework, the chapter introduces the main research questions addressed in this thesis and, finally, an outline on the structure of the remaining chapters. This thesis places itself among the various studies conducted in examining the effects of climate and price variability at the household level in the context of Sub-Saharan Africa (SSA).

#### **1.1** General introduction

Most farm households in many developing countries face climate risks in the form of drought, flood, pests and diseases, which affects both crop and livestock sectors that have limited possibilities to externalize risk through insurance mechanisms. Using a wide range of methods in many developing countries, previous studies further documented that the impacts of climate variability are largely negative for countries most dependant on the agricultural sector (Thiede, 2014; Deressa *et al.*, 2009; Di Falco *et al.*, 2011; Wossen *et al.*, 2014; Lobell *et al.*, 2008; Wheeler and von Braun, 2013; Cooper *et al.*, 2008; Thornton *et al.*, 2009; Hertel *et al.*, 2010). Even more so in SSA since natural resources and rain-fed agriculture, which are very sensitive to climate variability, form the basis of livelihood. In this regard both Ethiopia and Ghana are very vulnerable to the impacts of climate variability. For example, in the Upper East Region (UER) of Ghana, agriculture employs about 80% of the economically active population (GSS, 2010). Similarly, in Ethiopia and 80% of employment (MoFed, 2010).

In addition, to dependencies on climate sensitive livelihoods, both countries are sensitive to the impacts of climate variability due to the lack of adaptive capacity resulting from pervasive poverty<sup>1</sup>. Despite the impressive progress shown in Ghana, the Northern part of the country in general and UER in particular remained poor with a poverty rate of 73% in 2005/2006. In Ethiopia, poverty is also pervasive, with 29.6% of households still living under the poverty line (CSA, 2012). As such, with climate change and variability one can expect poverty and food insecurity to be exacerbated both in Ethiopia and Ghana. Differences in vulnerability might also be caused by differences in the extent of exposure to climate variability, sensitivity of households to the impacts of variability and the level of the household's adaptive capacity (Adger et al., 2005). In line with this, Busby et al. (2013) analyzed hot spots of climate variability in Africa and found considerable variation in vulnerability to climate change between and within countries. In particular Ethiopia and Ghana were found to be highly vulnerable to climate variability, with the northern parts of both countries being extremely vulnerable to the impacts of variability. In addition, since households differ in livelihood diversification strategies as well as in crop and livestock production potentials, impacts may vary considerably. While the impact on crop productivity is largely negative, its effect on livestock production is very complex and not yet clear. In fact, Martin et al. (2014) documented that climate variability can have negative, none or positive effects on livestock production.

Apart from climate variability, an increase in price variability has also been a main driver of food insecurity in Ethiopia and Ghana (Heady *et al.*, 2010; Alem and Söderbom, 2012; Ticci, 2011). Capturing the effect of price variability is crucial since expenditure on food represents a substantial share of consumption. For example, in rural Ethiopia the share of food expenditure from total expenditure is around 80% (ERHS, 2009). As such, changes in food price would lead to substantial changes in the food security status of farm households. However, capturing the effects of price changes and variability is a daunting task, as it requires estimation of a demand system (Attanasio *et al.*, 2013). The use of a demand system is necessary in capturing food security outcomes, as households may change their food composition by substituting food items based on changes in relative prices. In addition, the use of a demand system along with a parameterized production function becomes necessary, since the effects

<sup>1</sup> In addition, due to its tropical location, SSA is among the hottest places on the earth. Further warming due to climate variability and change will therefore have adverse impacts on crop productivity and food security (Adjaye, 2014).

of price variability and change on food security depends on the rate and speed of productivity-induced market price changes, the market position of households (net buyer vs. net seller) and the extent of market integration of farm households (Hertel *et al.*, 2010).

However, current studies with a focus on food security have developed into two independent streams, with one focusing on climate variability effects and the other on price variability effects, giving little attention on the co-variation between climate and price variability. While examining climate and price variability outcomes on food security, capturing co-variation in price and climate and estimating the combined effects on food security provides a prudent evaluation of policy interventions. In addition, capturing both drivers of food security allows policy makers to understand the magnitude and direction of each effect independently, as well as their combined effects. Analyzing the combined effects of climate and price variability is even more crucial since households might change their production decision due to food security priorities. In addition, it is very crucial to not only examine the magnitude and directions of the effects of variability at the disaggregated household level, but also the distribution of such effects. However, empirical studies so far have focused on analyzing impacts giving little attention to the differential effects of variability as well as adaptation options on food security and income among households. As a result, examining the effects of both climate and price variability as well as the current roles of adaptation strategies will be important in order to improve food security by designing prudent policy interventions.

Reducing climate and price variability induced food insecurity and poverty through effective adaptation options, requires considering the agricultural sector as the main driver of economic growth. For instance, Hertel and Rosch (2010) documented that growth in the agricultural sector of SSA is 2.2 times more effective than growth in non-agricultural sectors in reducing poverty and food insecurity. Therefore, reducing poverty and food insecurity under climate and price variability requires improving agricultural productivity through appropriate adaptation options. In the context of SSA, several studies have documented possible adaptation options along with their expected effects (Deressa *et al.*, 2009; Di Falco *et al.*, 2011; Wossen *et al.*, 2014; Bryan *et al.*, 2009). These studies underscored the need for capturing consumption and

production behaviour of households since adaptation requires altering current consumption and production trends due to the complex relationships between the biophysical and socio-economic processes. Parameterization of consumption and production behaviour of farm households is also important since households may resist potential shifts in consumption and production due to fear of the welfare consequences of climate variability as well as many other behavioural reasons such as preferences and risk aversion (Dercon and Christiaensen, 2011).

Further, given the prevalence of climate and price variability induced food insecurity in Ethiopia and Ghana and the increasingly complex risks farmers face, appropriate adaptation options such as diversification towards income sources that are less sensitive to climate variability as well as appropriate risk management strategies will be important in reducing the impacts of not only climate variability, but also price variability. Such an intervention is related to policy measures to reduce reliance on rain-fed agriculture through transformation of production systems as well as through the provision of off-farm wage employments. Off-farm wage employment is an important adaptation mechanism to climate and price variability, as agricultural practice is seasonal in many parts of SSA, including Ethiopia and Ghana. As such, households who have labour scarcity during the peak period may have surplus labour in the slack season (Bezu et al., 2014). With access to off-farm employment opportunities, labour can be hired during the peak periods to improve productivity, while it can also be released during the slack season to generate additional income. Such income generated from off-farm employment can be used to buy agricultural inputs in order to improve productivity or to buy food items from the local market to improve food security at times of variability. For example, Bezu et al. (2012) documented that households with access to off-farm income were able to use more fertilizer, enabling them to improve productivity, a critical component of food security.

However, co-variations may also exist between access to off-farm employment opportunities and climate variability. The effect of such co-variation is however not clear. For example Kijima *et al.* (2006) found that the share of off-farm labour supply increases with rainfall shocks. Similarly, Ito and Kurosaki (2009) documented that households respond to rainfall shocks by changing their labour supply decision. In

particular, they found strong evidence that off-farm labour can be used as an ex-ante income diversifying measure even though its role as an ex-post income diversification method is not robust. Even though variability may increase the decision to increase labour supply, it may also reduce the demand for it. In fact, Rosenzweig and Udry (2014) documented that a forecast of good weather lowers wages and exacerbates the negative impact of adverse weather. As a result, the overall effect of climate variability on wage income is not clear.

Another well documented problem that farm households face in the context of SSA is the lack of financial resources to make investments in order to improve agricultural productivity. In fact a number of studies in SSA documented a lack of credit as the main reason for the low use of agricultural inputs such as fertilizer, improved seed, irrigation and other productivity enhancing instruments. Relaxing such liquidity constraints therefore helps households make investments necessary to reduce the adverse impacts of variability. Empirical evidence in many developing countries revealed that access to credit improves the use of fertilizer, improved seed and irrigation (Wossen *et al.*, 2014). In particular, new technologies are expensive and require paying investment costs upfront. Without access to credit, poor farm households may not be able to finance these profitable options, including agricultural inputs such as improved seed, fertilizer and irrigation.

Adoption of new crop varieties that improve productivity is also another important adaptation option in the context of smallholders. For example Bezu *et al.* (2014) documented that a 1% increase in the area planted to modern maize varieties improves income and consumption by 0.48% and 0.34%, respectively. Similarly Shiferaw *et al.* (2014) documented that farm households who have adopted improved wheat varieties have better income and food security levels compared to those who did not adopt. In addition, using a regime switching regression approach, they documented that farm households that did adopt would have benefited significantly had they had adopted new wheat varieties. However, adoption of new varieties requires advanced knowledge of input management, which is usually distributed in package format (Dercon and Christiaensen, 2011). Furthermore adoption of new and improved varieties usually requires more investment in the form of irrigation, seed and fertilizer. However, these costs are irreversible, making adoption costly without appropriate policy supports. As

such, considering a portfolio of policy interventions, such as credit access, along with new crop varieties may become promising means for adapting to the impacts of climate and price variability.

Given that the current production and consumption behaviours are customized to current climate conditions, significant changes in production and consumption are inevitable due to climate variability. In this regard, adoption of new crop varieties that are suited to current climate variability will be essential in understanding the effects of future climate variability on consumption and food security. As Adger et al. (2005) argued, what constitutes an effective coping and adaptation is not clearly defined. For example, it has been documented that the sale of livestock is an effective way of coping and adapting to climate variability, at least in the short run. In the long run, however, it has also been shown to move households in to what is commonly termed as asset poverty trap. As a result, one has to first identify adaptation options that do not have long-term consequences at the expense of short-term gains. In this thesis, we considered such adaptation strategies as last resort options that households are typically reluctant to undertake. Developing effective adaptation options against the implications of climate variability may sometimes make little sense without also providing options that minimize price variability effects. Most of the adaptation options considered in this thesis can in fact also reduce the impacts of price variability. For example, credit and off-farm income are important to hedge against the vagaries of both climate and price variability.

#### **1.2** Methodological perspectives on impact assessment of climate variability

A wide range of methods, including simple cost-benefit analysis, empirical field survey methods, econometric (Ricardian) models, statistical models, partial and general equilibrium models, Agent Based Models (ABM) and process based-crop simulation models have been applied in examining the impacts of climate variability and change, as well the effectiveness of adaptation options (Nelson *et al.*, 2014; Di Falco and Veronesi, 2014; Troost and Berger, 2014; Berger and Troost, 2013; Wossen *et al.*, 2014; Arndt *et al.*, 2011; Lippert *et al.*, 2009). However, in analyzing the effects of climate variability, there is no doubt that integrated models are needed. All integrated models have so far agreed on the expected impacts of climate variability and change, but they differ significantly on the magnitude of such effects (Nelson *et al.*).

*al.*, 2014). These discrepancies are also partly attributed to the definition of impacts. Some models, for example Ricardian analysis of climate variability, take into account adaptation in the calculation of impacts while other models, such as crop growth models, do not.

While partial and general equilibrium models are designed to capture effects at global, national or regional level, ABM and Ricardian approaches are well suited to undertake impact assessment at the farm and household level. Since the focus of this thesis is to model climate variability effects at the household level, emphasis is given on the use of ABM. However, it is worth considering partial equilibrium models, when analyzing effects at the sectoral level (such as the agricultural sector). Similarly, general equilibrium models are suited for analysis of economy-wide effects of climate variability. Both partial and general equilibrium models of climate variability are not household level models, as they provide aggregate costs of climate change and variability. However, these models are able to captures the different pathways through which climate variability may affect the economy. These include productivity shocks, output and factor price changes, as well as effects through wage rates.

Crop growth models are process-based approaches to understand the impacts of climate variability and change on crop production systems (Lobell *et al.*, 2008). Such procedures have been applied in a wide range of crops and countries (Lobell *et al.*, 2008; Nelson *et al.*, 2014; Biggs *et al.*, 2013). Different varieties of crop growth simulation models have been applied for assessing the impacts of climate change. Among these, we utilized the FAO crop growth model "CROPWAT" for climate impact assessment in Ghana. The crop growth models were used to estimate the impacts of climate variability on crop yields, considering other management factors. The advantage of using crop growth models for capturing climate induced production shocks is that they are process-based applications. For example, DSSAT captures the effects of climate variables on crop yield on daily basis while CROPWAT was parameterized to capture effects on a monthly basis (see, Schreinemachers and Berger, 2011)<sup>2</sup>. In addition, such models allow for the specification of other management

<sup>&</sup>lt;sup>2</sup> Note the FAO crop-growth model as implemented in MPMAS is not a process-based model, as it was empirically approximated by using observed data using the USDA soil conservation formula.

techniques, such as the use of labour and fertilizer, along with climate variables for capturing production shocks.

In addition to process-based models of crop growth simulations, other statistical and econometric approaches have been extensively used for the assessment of climate impacts. Among these, the Ricardian approach pioneered by Mendelsohn *et al.* (1994) is the most widely used. The Ricardian method estimates the impacts of climate change by regressing land values or farm revenue on a set of climate variables and other exogenous controls<sup>3</sup> (Mendelsohn *et al.*, 1994; Di Falco, 2014, Lippert *et al.*, 2009). The major advantage of this methodology over pure process-based crop growth models is its ability to model adaptation while estimating climate variability effects. However, the use of Ricardian analysis has some limitations for the analysis of climate variability induced welfare changes due to the following reasons.

First, the use of cross section data for the analysis of impact assessment creates bias due to potential omitted variables. Although attempts has been made to reduce potential omitted variable impacts through the use of fixed-effect models, the majority of the studies conducted so far have been based on cross section data. Furthermore, the model assumes that climate change/variability effects are reflected in land rental values (Hertel and Rosch, 2010). However, this assumption may become bold since formal market for land are missing or under developed in many developing countries. In addition, the model relies on past observation assuming unchanged production structure and farmer behaviour. This lack of a processed-based underpinning makes longer-term predictions with these models questionable (Berger and Troost 2014). As such the model neither takes into account adjustment costs to the neither new climate nor impacts on household food security as it does not consider non-seprability in production and consumption.

Modelling food security and poverty under climate and price variability needs to take into account a large number of complex and interrelated factors that can only be captured through integrated household models (Troost and Berger, 2013). As such, a model capable of capturing the complex relationships between the biophysical and

<sup>&</sup>lt;sup>3</sup> Land values are used as dependent variables based on the assumption that in a competitive market, the price of farmland reflects the discounted value of all the expected future profits that can be derived from it (Mendelsohn *et al.*, 1994).

socio-economic processes, while also considering complexity and heterogeneity, will be crucial in examining climate and price variability effects in the context of smallholders in SSA. One such methodology is the use of ABM, which models decision-making processes while considering high degrees of heterogeneity, nonlinearity, interaction and feedbacks, and emergence (Berger, 2001). In this regard, we implemented an agent-based model called Mathematical Programming Based Multi-Agent System (MPMAS) that captures farm-level impacts of climate variability while capturing a wide range of adaptation options. In particular, MPMAS is an important tool for the farm-level assessment of climate variability impacts on food security and poverty by considering important micro-level constraints such as environmental externalities, limited adaptive capacity, and behavioural barriers (Berger and Troost, 2014).

MPMAS is able to represent uncertainty in production and consumption decisionmaking processes, is flexible enough for impact assessment, captures causes and outcomes of adaptation processes due to its recursive nature, and assesses tradeoffs and synergies between food production, consumption (and hence food security) and environmental impacts resulting from the use of adaptation options. Furthermore, the model is very strong in the quantification of consequences from variations across different households in terms of resource and wealth dynamics, adaptive capacity, production and consumption preference, knowledge and learning ability. Since MPMAS captures farm level costs explicitly, adaptation to climate variability occurs endogenously. Furthermore, by incorporating interactions and feedbacks between the socio-economic and biophysical processes, MPMAS is able to capture the biophysical (climate variability) impacts on socio-economic process (food security, poverty, etc.).

In addition, MPMAS treats agents as autonomous decision makers and allows a great deal of flexibility in how decision-making processes are represented (Berger and Troost, 2014). In addition, by explicitly capturing agent to agent and agent to environment interactions, MPMAS becomes crucial for modelling technologies for reducing climate variability impacts. Agent to agent interactions is related to interactions between agents for sharing resources and information for technology adoption. This involves an agent receiving information about (being exposed to) new agricultural technologies. For the case of Ethiopia and Ghana, the crucial effect of

agent to agent interactions was captured by using a network threshold approach. In addition, MPMAS was parameterized using econometric techniques (based on adoption thresholds as estimated based on the time lag and adoption probabilities) in order to determine agent to agent interactions for adoption of adaptation strategies.

Since adoption of risk reducing adaptation strategies against the adverse impacts of climate variability requires agent to agent interactions in which heterogeneity between agents and social relationships play a significant role, the use of MPMAS will be appropriate (Berger and Troost, 2014). Another aspect of complexity that is captured in ABM is agent to environment interactions. As implemented now, agents influence the environment through their land use and input decisions, while the environment influences agents by returning a level of crop yield, which is a function of input decisions and environmental processes such as weather, water flows, and soil nutrients (Schreinemachers and Berger, 2011). In addition, MPMAS is able to mix simple heuristic and optimization techniques in capturing agent to agent interaction. By doing so, it exploits the advantages of optimization models while reducing reliance on a rational decision-maker with perfect foresight as opposed to bounded rational agents (Schreinemachers and Berger, 2006).

### **1.3** Conceptual framework

We identified different pathways through which climate and price variability may affect household welfare in Ethiopia and Ghana. In particular we considered the following pathways: impacts on household food security and poverty, impacts on household income, impacts on agricultural input use and impacts on livestock holding. Other pathways, such as through non-priced goods and damages to infrastructures, are not captured in this thesis. After establishing the pathways as well as the magnitudes of climate and price variability effects on household food security and poverty, the thesis then proceeds in examining the effectiveness of adaptation options-both autonomous and planned ones, including the distributional effects of such interventions.

Food security is a complex issue that requires an all-encompassing measurement and definition. The most widely used and accepted definition of food security is based on the 1996 World Food Summit. Accordingly, food security exists *"when all people, at* 

all times, have physical, social and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life" (FAO, 1996). The above definition encompasses the availability, access, stability and utilization pillars of food security. These pillars of food security are naturally linked and can be viewed at the global, national, household or individual level. Achieving food security at the national level is necessary but not sufficient, to ensure household food security (Barrett, 2010; Wheeler and von Braun, 2013). The conceptual framework in Figure 1.1 shows the link between variability, possible adaptation options and food security outcomes.

Climate variability manifested by changes in rainfall amount, intensity and timing, as well as through changes in temperature, affects food security outcomes through many pathways. Depending on the severity of climate variability and the adaptation options undertaken by households, climate variability effects will be manifested in terms of changes in crop yields. Changes in crop yield then directly affect the availability component of food security. However, impacts on crop yield could also be reduced through appropriate adaptation strategies. The extent of rainfall variability, for example, shapes the kind of adaptation strategies adopted by households. With extreme variability, households may make use of off-farm employment options or adopt risk-mitigating strategies, such as soil and water conservation practices.

The kind of adaptation strategies adopted by farm households is also affected by the adaptive capacity of those households, which is in turn affected by the household's resource endowment. Differences in access to the different components of capital and resource endowments are important in shaping not only the type of adaptation options available to households but also the intensity and effectiveness of such adaptation options. As such, the use of ABM is crucial in capturing differences in adaptive capacity among households, as they are different in access and possession of the different component of social capital (natural, physical, social etc.).



Figure 1.1: Conceptual framework

#### Based on: Chijioke et al., (2011)

The other pathway through which climate variability affects food security is through changes in relative prices. Since high climate variability affects the supply of food products, it is easy to see that it will have an effect on food security through what is commonly called climate-induced price variability. The problem of price variability can however be persistent even without climate variability due to changes in domestic policies, exchange rates, trade policies and other factors. As a result, while examining outcomes such as food security, it will be important to capture both climate-induced and non-climate-induced price variability. Price variability on output prices, input prices and wages affects food security in many ways. First, changes in output prices affects crop choice and production decisions of farm-households, and hence productivity of crops and food security. Second, changes in the relative price of inputs such as fertilizer and seed affects input-use decisions, and hence crop productivity and food security. And finally, changes in wage rates affect the household's ability to access food. Even though climate variability is widely expected to affect productivity and food security adversely, the impacts of price variability are not clear. The effects of such price variability therefore depend on the magnitude of productivity shocks, the rate and speed of productivity induced market price changes, the market position of households (net buyer vs. net seller) and the extent of market integration of farm households.

Prudent institutions and the policy environment are also important in reducing the impact of climate and price variability and hence improving food security. On one hand, the extent of variability affects the type of policy directions. On the other hand, institutional capacity and policy environment are crucial in reducing the impact of variability. In addition, institutional capacity and the policy environment also affect the type and extent of adaptation strategies undertaken by households. For example, the strength and ability of institutions determines whether households can adopt new crop varieties and access short-term credit or off-farm employment options. Policy and institutional set-ups are also important in reducing climate variability impacts on food security, for example through food aid and other relief programs.

The other very important aspect of adaptation options in light of climate variability is reliance on informal social networks in providing insurance against shocks. It has been documented that some forms of informal social links and organizations have an explicit insurance component against shocks. For example, the *Iddir* in the Ethiopian case provides in-kind and financial assistance in times of hardship with no to very low interest rates. Furthermore, some aspects of social capital and extended kinship networks help to insure consumption against shocks through moral obligation, sharing and redistribution of resources (Di Falco and Bulte, 2013). Given that formal risk-sharing mechanisms are largely limited in many developing countries, including Ethiopia and Ghana, we expect social capital to be helpful in maintaining consumption in the face of rainfall shocks. As such capturing the roles of informal social networks and social capital on the household's ability to insure food security under variability will be very important.

In addition, social capital and informal social links are important in enhancing adoption of risk mitigation land management strategies in order to reduce the impacts of climate variability. An individual's access to social capital impacts adoption of risk-mitigating land management practices by reducing some of the prevailing market inefficiencies and supply-side constraints of adoption. Examples of market imperfections that impede adoption of risk mitigating strategies that may be reduced through social capital include missing markets for risk, credit, labour and information (Jack, 2011; Shiferaw *et al.*, 2009). In particular, in the absence of well-functioning formal labour, credit and information markets, social capital enhances adoption by

helping individual adopters to overcome their labour and cash constraints (Krishna, 2001) and by facilitating the flow of information by reducing asymmetric information and transaction costs (Abdulai *et al.*, 2008).



Figure 1.2: Decision on undertaking adaptation strategies

Source: Adapted from Berger and Troost, 2013.

Figure 1.2 above further shows how adaptation options undertaken by households are implemented in MPMAS. Given that we consider adaptation option triggered by variability, the necessary condition is experiencing variability. Having experienced variability, households have a choice either to undertake adaptation option or face the full effects of variability (no adaption taken). The decision to undertake adaptation strategies depends among other things on adaptive capacity, availability of options, extent of variability and other factors. Undertaking adaptation, however, may not necessarily reduce the impacts of variability, as options might turn out to be ineffective. As a result, adaptation options will be effective so long as they can at least partially reduce the effects of variability and hence improve household food security. Using a conceptual framework developed by Antle and Capalbo (2010), we further explained how the impacts of variability and the effectiveness of policy interventions are examined.



Figure 1.3: Evaluation of the effectiveness of adaptation options Source: Based on Antle and Capalbo (2010)

Figure 1.3 above is a generic representation of how the effectiveness of adaptation options are evaluated in chapter 2 and 3 of this thesis. Y represents an outcome variable measured to evaluate the impacts of climate and price variability (in our case mainly that of household income and food security).  $A_i$ ,  $[1 \cdots n]$ , represents the different set of adaptation options available to a given household while  $C_0P_0$  represents the hypothetical situation of no climate and price variability. Point b represents the income or food security level of farm households at current level of adaptation  $(A_0)$ under no climate and price variability. With the same level of adaptation, point d then represents the level of income or food security that a given household achieved under climate and price variability. The impact of climate and price variability is represented by the vertical distance (b-d). In order to reduce the impacts of variability, households may respond by increasing the scale of their adaptation through the use of more credit, off-farm income or adoption of new and improved seed varieties which is represented by  $(A_1)$ . Under the new level of adaptation, the level of income or food security achieved by a household is given at point g and the corresponding effect of climate and price variability is given by (f-g). The difference (g-h) implies the role of adaptation strategies. In the extreme scenario, when the scale of adaptation reaches

 $(A_2)$ , adaptation not only successfully reduces the impacts of variability but also improves food security and income beyond the initial condition.

### **1.4 Objective of the study**

The general objective of this thesis is to perform a household-level simulation study on the impacts of climate and price variability on food security and poverty in Ethiopia and Ghana. In addition, the study examines the effects of local links and networks on consumption smoothing and adoption of risk mitigating technologies in Ethiopia. The first part of the study focuses on agent-based modelling of climate and price variability effects and the effectiveness of adaption option-both autonomous and planned options in terms of reducing food insecurity and poverty. The second part of the thesis considers the roles of social capital and informal social networks on consumption insurance and adoption of risk mitigating technologies in the form of land management practices. The specific research questions addressed in the four interrelated articles are presented below.

Research topic 1: Climate Variability, Food Security and Poverty: Agent-Based Assessment of Policy Options for Farm Households in Northern Ghana.

This study applies an agent-based modelling approach to examine the impacts of current climate and price variability on food security and poverty with the following research questions:

1. What are the likely impacts of climate and price variability on household food security?

Using data from the 2005/06 Ghana Living Standard Survey(GLSS5) and the CGIAR Challenge Program on Water and Food(CPWF), along with detailed local level price and rainfall data, the study quantifies climate and price variability effects at the household level using an ABM approach. In addition, the study investigates to what extent and for whom variability matters with regards to food security, as well as whether the effects of variability are distributed uniformly.

2. How would policy interventions, especially those related to the promotion of credit and off-farm employment, affect the distribution of food security under climate

and price variability?

In addressing the above policy-relevant research question, we examined the roles of policy options for reducing variability impacts given the current state of technology and institutional frameworks by differentiating between those that can be undertaken by farm households themselves (e.g., use of livestock, altering production and consumption behaviour) and those that involve policy interventions (e.g., provision of credit and off-farm employment opportunities). In particular, by simulating food security and poverty levels under current climate and price variability, including policy scenarios for credit access and off-farm income opportunities, the study aims to identify potential entry points for specific adaptation policies that can increase the resilience of smallholder farmers facing increasing climate variability in the future.

Research topic 2: Can small holder farmers adapt to climate variability, and how effective are policy interventions? Micro-simulation results for Ethiopia

Using the same agent-based approach, the study aims at addressing two broad relevant questions regarding the impact of climate and price variability in Ethiopia:

1. What are the likely impacts of current climate and price variability on household food security?

By prametrizing a stochastic ABM using socio-economic data from the ERHS (2009), the study examines the impacts of current climate and price variability on farm household welfare in Ethiopia. In addition to examining variability effects, the study investigates the distributional impacts of such variability. The study further identifies the socio-economic characteristics responsible for variation across households in terms of their ability to successfully adapt and cope with climate and price variability effects.

2. To what extent do different current adaptation strategies buffer climate and price variability effects?

This objective is particularly crucial since investments in adaptation options are costly and hence the optimal level of adaptation could well be different among heterogeneous agents. In this regard, this paper aims to expand current literature on climate variability by considering the following relevant questions: How can institutional
arrangements related the promotion of credit, modern inputs and new crop varieties be effective under increasing climate variability in terms of enhancing productivity and food security? Are strategies composed of a portfolio of actions (such as credit and fertilizer subsidy along with new technologies) effective compared to a single action of intervention?

Research topic 3: Social Capital, Risk Preference and Adoption of Improved Farm Land Management Practices in Ethiopia.

While the previous two articles address the impacts of climate variability using an agent-based approach, this paper employs an econometric model to examine the following research questions:

1. How do the different aspects of social capital affect adoption of risk-mitigating land management?

Studies in Ethiopia suggest that adoption of land management practices and especially soil and water conservation measures are profitable (Kassie et al., 2010). Yet, adoption rates of such profitable land management practices remain critically low (Shiferaw et al., 2009), which raises the question of why adoption rates of profitable technologies would not become much higher. However, most adoption studies on land management practices with a focus on economic incentives pay little attention to the role of social capital. In the absence of well-functioning formal labour, credit and information markets, social capital may enhance adoption by helping individual adopters reduce asymmetric information and overcome labour and liquidity constraints of adoption. Specifically, we hypothesize that when lack of credit, labour and information are limiting factors for adoption, social capital will have a positive effect on adoption by relaxing cash, labour and information constraints that a given farmer faces when making investments in new land management practices. We further hypothesize that when insurance markets are absent or inefficient, social capital enhances adoption by reducing uncertainty about new technologies (Abdulai et al., 2008). Finally, we expect social capital to have a negative effect when individual adopters have to share the benefits from adoption but bear the investment costs of adoption.

2. Is the effect of social capital across households holding different levels of risk attitudes the same?

The effect of risk-aversion on the adoption of land management strategies is well documented (Teklewold and Kohlin, 2012). However, there appears to be a scarcity of empirical studies that address the effects of social capital across households holding different levels of risk attitudes. This is particularly important since heterogeneity of risk attitudes might affect the formation of social capital and groups. We hypothesize that if risk-aversion affects the formation of links and networks, then the effect of social capital across households holding heterogeneous risk attitude levels could be very different.

3. Can access to formal credit crowd out the effect of social capital on technology adoption?

Access to credit is quite instrumental in relaxing the liquidity requirements necessary to make investments in land management practices. Most formal credit markets, however, systematically exclude the poorest households (Bhattamishra and Barrett, 2010). In the absence of formal credit markets, the poorest of the poor may therefore rely on their social capital to relax financial and labour constraints. In this regard, we hypothesize that the crucial role of social capital declines as households gain access to formal credit.

Research topic 4: Social Capital, Household Welfare and Consumption Smoothing: Evidence from Rural Ethiopia.

This paper focuses on Ethiopia and examines the extent to which social networks contribute to maintaining household consumption when challenged by shocks. Specifically, the study aims at addressing the following research questions:

1. To what extent do informal social networks and social capital help households insure consumption (food security) at times of rainfall and health shocks?

In addressing the above objective, we investigate whether large network sizes (measured by the self-reported relationships with individuals whom a given household considers to be very important at times of hardship, from both within and outside the village) and membership to *Iddir* (a form of bridging social capital in Ethiopia) help households enhance welfare and insure consumption against rainfall and health shocks. We hypothesizes that households with better social capital are able to smooth

consumption at times of both covariate (e.g. rainfall) and idiosyncratic (e.g. health) shocks.

2. To examine the interaction effect between different social capital indicators and shocks experienced by farm households.

It has been well documented that access to formal financial markets can help households accumulate wealth, even at times of unfavourable rainfall distribution. For example, Islam and Maitra (2012) found that households with microcredit access are less likely to disinvest by selling livestock in response to health shocks, allowing them to avoid poverty traps. In this regard, we hypothesize that households with better social capital are less likely to sell livestock assets in order to cope with the effects of shocks.

## **1.5** Outline of the thesis

The structure of this thesis is as follows. Chapter 2 to 5 corresponds to four journal articles that each address one of the four research topics identified above. Two of these articles have been accepted for publication at *Agricultural Economics* and *Environmental Science &Policy*, two papers are currently in review. The first article (chapter 2) aims to understand the effect of climate variability on food security and poverty and identify effective adaptation measures in the context of subsistence agriculture in Ghana. Particularly, the study develops a micro-level simulation model building on the approach and data developed within a research project of the CGIAR Challenge Program on Water and Food. Specifically, the study applied agent-based modelling to analyze how farmer adaptation affects the distribution of household food security and poverty under current climate and price variability and examines to which degree policy interventions related to the promotion of improved credit and off-farm employment can be effective.

The second article (chapter 3) presents a stochastic bio-economic household modelling to analyze smallholder adaptation to increasing climate variability in Ethiopia. Specifically, the study used an agent-based simulation package that allowed for capturing non-separable production and consumption decisions, the role of livestock for consumption smoothing, default on credit, and temporary food shortages, as well as policy options related to the promotion of new crop varieties such as innovation diffusion, credit and fertilizer subsidies.

The third article (chapter 4) focuses on examining the impacts of social capital on the adoption of risk-mitigation technologies by considering the specific case of adaptation through land management practices in Ethiopia. It provides evidence of the effects of different dimensions of social capital on innovation adoption across households facing different levels of risk. By combining household panel data, weather data and detailed social capital information, the fourth article (chapter 5) examines how social capital can buffer some of the implications of weather and health shocks. In particular, this chapter aims to fill the research gap by investigating whether having large network size (measured by the self-reported relationships with individuals whom a given household considers to be very important in times of hardship, from both within and outside the village) and membership to *Iddir* (a form of bridging social capital in Ethiopia) help households enhance welfare and insure consumption against covariate and idiosyncratic shocks.

Finally, chapter 6 summarizes key findings and the implications of climate and price variability on food security outcomes. In particular, the section describes the contribution of this study and provides an outlook on future research areas.

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# **Chapter Two**

2 Climate Variability, Food Security and Poverty: Agent-Based Assessment of Policy Options for Farm Households in Northern Ghana.

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#### Abstract

According to the majority of regional climate projections, Sub-Saharan Africa (SSA) will likely become warmer in the next decades and rainfall patterns will substantially shift. Understanding the effect of climate variability on food security and poverty and identifying effective adaptation measures in the context of subsistence agriculture is imperative to ensure food security now and in the future. This paper presents a microlevel simulation study that was undertaken for Northern Ghana, building on the approach and data developed within a research project of the CGIAR Challenge Program on Water and Food. The study applied agent-based modelling to analyze how adaptation affects the distribution of household food security and poverty under current climate and price variability. Specifically, we examined the effectiveness of policy interventions related to the promotion of agricultural credit and off-farm employment opportunities. Our simulation experiments suggest that both climate and price variability have a pronounced negative effect on household welfare. Moreover, we found substantial difference in the poverty and food security status of households due to climate and price variability. Provision of agricultural credit and access to offfarm employment are found to be highly effective policy entry points that deserve more empirical research.

Keywords: food security, climate impact assessment, mixed rain-fed agriculture, bioeconomic modelling, policy simulation, multi-agent systems

## 2.1 Introduction

Although current data and models used for climate impact research still contain large uncertainties, most studies undertaken so far suggest that climate variability will aggravate the existing vulnerability of smallholder farmers in SSA (Nelson et al., 2009; Parry et al., 2004; Knox et al., 2012; Cooper et al., 2008). For the Volta basin in West Africa, for example, Jung and Kunstmann (2007) expect on average a 1.2 to 1.3 °C increase in temperature and a 5% increase in annual rainfall, with high spatial variation ranging from -20% to 50%. For agricultural production, it is usually more important when exactly it rains rather than yearly averages. In this respect, Jung and Kunstmann's simulations of future climate suggest a reduction of rainfall of up to 70% at the onset of the rainy season, when farmers are most dependent on adequate soil moisture to begin sowing their crops. These changes in future rainfall patterns might therefore have highly negative impacts on food security and poverty levels in a region that is already struggling with low agricultural productivity, little investment, and limited ability to cope with shocks. In a systematic mapping exercise for the entire African continent, Thornton et al. (2008) overlaid hotspots of climate hazards and hotspots of current vulnerability to identify geographical areas that appear most threatened by the emerging reality of climate change. Accordingly, the arid to semiarid parts of Northern Ghana, with their mixed rain-fed crop-livestock systems, are marked as high-risk areas demanding immediate and sustained research and development efforts.

As Arribas *et al.* (2011) stated: "*There is no better way of adapting to climate change tomorrow than adapting to climate variability today*". A useful way to prepare for uncertain future climate conditions is therefore to learn from current climate variability by simulating its impacts on crop yields and food security and by testing suitable policy interventions to improve resilience of smallholder farmers (Cooper *et al.*, 2008). In this regard, process-based models with biophysical and socio-economic components will be crucial to assess the impacts of climate variability on crop productivity, a key determinant of food availability. Previous studies by Di Falco *et al.* (2011); Swallow (2005); Hatch and Smith (1997); Hansen *et al.* (1988); Wheeler and von Braun (2013); Thornton *et al.* (2009); Briner *et al.* (2012); Bobojonov and Hassan (2014) have documented that climate variability poses threats to food security through its adverse effect on crop productivity. However, as indicated by Hertel *et al.* (2010),

productivity changes alone are a flawed indicator for the full adversity of climate variability, as the overall effect of climate variability on food security depends on the magnitude of productivity shocks, the rate and speed of productivity induced market price changes, the market position of households (net buyer vs. net seller) and the extent of market integration of farm households. If appropriately targeted policy interventions that can offset the potential adverse effects of climate variability are to be designed, it is crucial to analyze these effects by considering heterogeneity in policy responsiveness among farm households.

Despite the progress in integrated assessments of climate variability effects, most climate-related crop simulation studies to date have focused on crop yields only, giving little attention to the linkages between crop and livestock sub-systems and the key role that livestock play in the coping-strategies of many smallholder households in SSA (Thornton *et al.*, 2009; Claessens *et al.*, 2012). Other studies have also used macro-level models (e.g., Mideksa, 2010) or Ricardian analysis (e.g., Mendelsohn and Reinsborough, 2007). However, the aforementioned studies on the impact of climate variability may hide a great deal of heterogeneity, as smallholder farmers differ in access to resources, poverty levels, and their adaptive capacity to climate variability. As such, addressing the effectiveness of adaptation policies by capturing heterogeneity in terms of adaptive capacity will be crucial.

In addressing the challenges of climate variability, new assessments and fresh ideas are therefore needed to identify appropriate development and policy interventions that could better support current responses to climate variability that strengthen the adaptive capacity of smallholder farmers in the future. In this regard, micro-level assessments that take into account heterogeneity and interactions among smallholder farmers will be crucial to capturing the full distribution of constraints, opportunities, and responses of smallholder agriculture (Berger and Troost, 2013). One such methodology is the use of an Agent-based Model (ABM)<sup>4</sup>, as it offers the ability to explicitly simulate decision-making processes while considering high degrees of heterogeneity, nonlinearity, interaction and feedbacks, and emergence (Berger, 2001). In this paper, we present a stochastic ABM that is capable of simulating the effects of

<sup>&</sup>lt;sup>4</sup> In this study we used agent-based and multi-agent-based interchangeably.

different adaptation options by capturing the dynamic changes in climate and prices, as well as the dynamic adaptive process of different farm households to the impacts of these changes. The ABM was applied and validated for Northern Ghana, building on the approach and data developed within a research project of the Consultative Group on International Agricultural Research (CGIAR) Challenge Program on Water & Food (CPWF). The approach employed in this ABM captures non-separable<sup>5</sup> household decisions, livestock management, crop growth, policy responses, and innovation diffusion. As food security is a critical issue, the ABM employed in this study gives special consideration to the quantification and analysis of food security outcomes, a critical policy issue in Ghana.

Specially, the study aims at addressing three broad relevant questions regarding the impact of climate and price variability. First, by quantifying climate and price variability effects at agent level, it examines to what extent and for whom variability matters with regards to food security, as well as whether the effects of variability are distributed uniformly. Second, it examines policy options for reducing variability impacts given the current state of technology and institutional frameworks by differentiating between those that can be undertaken by farm households themselves(e.g., use of livestock, altering production and consumption behaviour) and those that involve policy interventions (e.g., provision of credit and off-farm employment opportunities<sup>6</sup>). Finally, the study addresses the effectiveness of these interventions at the agent level. In particular, by simulating food security and poverty levels under current climate and price variability, including policy scenarios for credit access and off-farm income opportunities, the study identifies potential entry points

<sup>&</sup>lt;sup>5</sup> Assumption of separability in production and consumption implies that a household's decision regarding production is not affected by consumption preference (Schreinemachers and Berger, 2011). However, the assumption of separability in consumption and production is misleading, since climate-induced changes in production require farm households to adapt their consumption behavior by shifting towards goods that are less sensitive to climate variability, which clearly affects welfare level. Moreover, a non-separable modeling setup is required since rural households in many developing countries are both producers and consumers with prevalent market imperfections (Sadoulet and de Janvry, 1995; Mideksa, 2010).

<sup>&</sup>lt;sup>6</sup> Provision of credit and off-farm employment opportunities were identified as potential entry points based on expert opinions in the CPWF project as well as studies by Yilma (2008).

for specific adaptation policies that can increase the resilience of smallholder farmers facing increasing climate variability in the future. The paper is organized as follows: section 2.2 briefly introduces the study area along with the data sources and methods used; section 2.3 presents the results from model validation and scenario analysis; section 2.4 and 2.5 discusses our findings and their relevance for climate impact assessments, and section 2.6 concludes with a list of open questions and an outlook on next research steps.

## 2.2 Data Sources and methodology

## 2.2.1 Study area

As mentioned in the introduction, the simulation study undertaken here builds on the data and models developed in the project "Integrating Governance and Modelling" within the CGIAR Challenge Program on Water and Food<sup>7</sup>. The study area is located in the Upper East Region  $(UER)^8$  of Ghana, the poorest of the 10 regions in Ghana (Gyasi et al., 2006), close to the city of Bolgatanga. The poverty level of 70% in UER is high compared to the national level of 28%. Moreover, the region is relatively densely populated: 104 people per  $\text{km}^2$  as compared to the national average of 75 people per  $km^2$  (GSS, 2004). Agriculture in the region is characterized by an unfavourable biophysical environment with frequent failure and uneven distribution of rainfall, rather poor soil quality and, often, land degradation. Apart from these adverse biophysical conditions, lack of access to credit and insurance markets, high costs of inputs and poor economic infrastructure are prevalent (Yilma et al., 2008). Farm households are mainly subsistence oriented and grow rain-fed crops in the rainy season (April to September) and irrigated crops in the dry season (November to March). The main food crops are rice, millet, groundnut, maize and beans, all rain-fed; the main cash crops are tomato, onion and leafy vegetables, which are cultivated in the dry season under irrigation. In addition to crop production, livestock wealth also serves as a source of nutritious food, transportation of farm outputs and inputs, and as a store of value in the absence of formal financial institutions. The main livestock

<sup>&</sup>lt;sup>7</sup> More background information about the study area including maps can be found at the project website <a href="http://www.uni-hohenheim.de/igm>">http://www.uni-hohenheim.de/igm></a>

<sup>&</sup>lt;sup>8</sup> Note that the northern part of Ghana consists of three regions: northern, upper east and upper west.

types kept in the study area include cattle and small ruminants such as goats and sheep.

#### 2.2.2 Data source

The data used in this study originate from the 2005/06 Ghana Living Standard Survey (GLSS5) and from the CGIAR Challenge Program on Water and Food (CPWF). The GLSS5<sup>9</sup> data set. a nationally representative survey of 8,687 households, was used to estimate household consumption patterns, while data on disaggregated monthly regional prices as well as daily precipitation and temperature were obtained from the CPWF. In addition, we used detailed data from 292 randomly sampled farm households of the CPWF project household survey to parameterize production behavior, demographic composition, agent endowments and geographical location of farm households. Using the Monte Carlo approach of Berger and Schreinemachers (2006), we created a 'synthetic' agent population of 1,609 households. In the model, each computational agent represents a single farm household in the study area; hence, there are as many agents in the model as there are farm households in reality. The agent population includes mostly agents with only rain-fed plots but some agents have access to small-scale irrigation and large-scale irrigation. Econometric techniques were used to parameterize consumption and production decisions of farm households, while agentbased simulation (see Nolan et al., 2009) was used for analysis of the complex mixed rain-fed crop-livestock system. Examples of agent-based simulation of climate impacts are Bharwani et al.(2005); Ziervogel et al. (2006); Acosta-Michlik and Espaldon (2008); Angus et al. (2009); Hailegiorgis et al. (2010); Janmaat and Anputhas (2010); Kniveton et al. (2011); Troost et al. (2012); Aurbacher et al. (2013); and Wang et al. (2013).

#### 2.2.3 MPMAS as a tool for climate variability analysis

Mathematical Programming-based Multi-Agent Systems (MPMAS) is an agent-based simulation package using whole-farm mathematical programming to simulate farmer decision-making in agricultural systems (Schreinemachers and Berger, 2011). It employs scenario-based analyses to examine the possible impacts of exogenous

<sup>&</sup>lt;sup>9</sup> The GLSS5 contains detailed information of demographic characteristics of the population, education, health, employment and time use, migration, housing conditions and farming.

changes such as climate and price variability on household welfare. The main strength of MPMAS is its ability to capture agent and landscape heterogeneity, spatial interactions and social interactions (such as resource and information sharing), technology and market dynamics, and environmental changes (van Wijk *et al.*, 2012). The studies of Berger (2001); Schreinemachers *et al.*(2007); Berger *et al.* (2007); Schreinemachers *et al.*(2010); Marohn *et al.*(2013); and Quang *et al.*(2014) demonstrate the empirical use of MPMAS in developing countries. For this particular study we used the components of MPMAS most relevant for climate variability analysis<sup>10</sup>. The software architecture of MPMAS has been described in Schreinemachers and Berger (2011) following the ODD-protocol and is therefore not repeated in this paper. Technical documentations, executable programs and software manuals can be downloaded from https://mp-mas.uni-hohenheim.de.

Climate variability affects household income in many ways, notably through changes in crop yield, price, rural wages and productivity (Hertel et al., 2010). Like many other conventional bioeconomic household models, MPMAS is able to capture climaterelated effects in great detail (Berger and Troost, 2013). However, MPMAS has the added advantage of combining economic, environmental and social components at fine resolution with dynamic interactions between agents (Schreinemachers and Berger, 2011; Berger, 2001; Berger and Troost, 2013). MPMAS incorporates extensive module components, such as a socio-economic decision module, communication network module, consumption module and crop growth module, for climate impact analysis (Berger, 2001; Schreinemachers et al., 2007; Schreinemachers and Berger, 2011). The agent-based decision module, for example, captures farmer investment decisions (such as growing perennial crops, keeping livestock, acquisition of land and machinery etc.), production decisions (e.g., allocation of land for annual crops) and consumption decisions (selling crops, buying food etc.) in a non-separable setup using Mixed Integer Linear Programming (MILP). Since agents are heterogeneous, the optimization procedure is agent-specific and differs in terms of internal MILP coefficients (e.g., expected yields and consumption shares) and agent resource endowments.

<sup>&</sup>lt;sup>10</sup> This includes a market module, network module, population and demography module, crop growth module, livestock module and perennial crops module.

Human-environmental interactions are captured through climate variability effects on agricultural productivity. Impacts from agricultural production decisions on the environment are reflected in terms of resource use and exploitation, while the feedback from the environment to agents is transmitted through yield changes. Agents in MPMAS are affected by climate variability through changes in crop yields, which creates an incentive to adjust crop choice and input levels or to adopt soil and water conservation techniques (Schreinemachers and Berger, 2011). The advantage of using MPMAS over other bio-economic models is that the effect of climate variability is agent specific, as agents are heterogeneous in terms of resource endowments and adapting capacity.

The crop-specific effect of climate variability on yields was captured through the biophysical model CROPWAT. CROPWAT is integrated in MPMAS and as such all agents send their production decision at the beginning of the year for CROPWAT and then CROPWAT sends back the expected yields to agents. Since the choice of cropmix is agent-specific, individual household agents achieve different levels of yield based on their production decision. The agent choice of crop-mix depends, among other parameters, on expected yields, expected market prices, actual input prices, and initial agent resource endowments. During simulation, agents may then adapt through adjusting their resource use (e.g. land, labour, livestock, etc.). We included in our decisions module monthly land, labour, and water constraints to capture multiple cropping, peak labour needs and monthly variations in irrigation water supply.

Climate variability induced yield changes affect consumption in many ways, notably through changes in price, rural wages and productivity (Hertel *et al.*, 2010). In this study, the consumption behaviour of model agents was parameterized using a three-stage budgeting process (Figure 2.1), building on the approach for smallholder farmers developed by Schreinemachers *et al.* (2007). First, agents make a decision on how to allocate achieved income into savings and expenditure. Second, a decision is made on how to allocate expenditures between food and non-food items. Third, agents decide on the allocation of food expenditures into different types of food categories, taking into consideration their consumption preferences, the price of goods, and other factors such as age and gender of household members.

In this agent decision process, climate-induced yield changes are translated into consumption vulnerability through changes in the quantity of food available for consumption and changes in income. Consumption requirements have to be satisfied through income generating activates by the agent and disinvestment options, such as using savings and selling livestock, to achieve minimum consumption requirements. Since agents make their consumption decisions after income has been earned and all loans repaid, MPMAS uses a parameterized version of the Almost Ideal Demand System (AIDS-Deaton and Muellbauer, 1980) to translate the effects of climate variability into consumption vulnerability at agent level.



Figure 2.1: Flow chart of MPMAS decision module

Source: Adapted from Schreinemachers and Berger (2011)

The point of departure is the standard economic relationship between savings and income: total income Y is equal to the sum of savings S and total expenditure TE (see details in Schreinemachers *et al.*, 2007):

$$Y = S + TE \tag{1}.$$

For an individual household agent, savings are specified at stage one as a function of income and other household specific characteristics such as age and gender of its

members. For this study, the following quadratic specification of the savings function was used:

$$S = \alpha_0 + \beta_1 Y + \beta_2 Y^2 + \beta_3 x^{hc} + \sum_{n=1}^n \beta_n D + \mu_i$$
(2).

where S is total savings from a given level of income, Y is the total disposable income,  $x^{hc}$  includes a vector of household characteristics such as household size and D is a vector of regional dummies to capture differences in saving behaviour. The above savings function was parameterized using income and expenditure data from the GLSS5 data set.

The second stage of the budgeting process, where agents allocate total expenditure to food and non-food expenditures, is captured using a modified version of the Working-Leser model, following Schreinemachers *et al.* (2007). Our Working-Leser specification considers commodity budget shares as a function of the logarithm of per-capita expenditure and was specified as follows:

$$\omega_{i} = \alpha_{0} + \beta_{1} \ln(PCE) + \beta_{2} x^{hc} + \sum_{n=1}^{n} \beta_{n} D + \mu_{i}$$
(3).

where  $\omega_i$  is the share of food expenditure from the total expenditure, *PCE* is per capita expenditure,  $x^{hc}$  is a vector of household characteristics and *D* is a vector of regional dummies to capture differences in expenditure. Also, the Working-Leser model was estimated using GLSS5 expenditure data, in which information on different sources of income, food and non-food expenditures were recorded. Household food consumption is comprised of monetary expenditures on food, quantity of consumption from own harvest, and gifts. The quantity of own consumption was converted into imputed values using the community-level price information of food items.

The final stage of the budgeting process involves the agent decision to allocate food expenditures to specific food items. This stage was parameterized in MPMAS with a budget share equation for each food category specified as a function of its own price, the price of other goods in the demands system and the real total expenditure on the group of food items:

$$\omega_{i} = w_{i} = \alpha_{0} + \sum_{j=1}^{j} \gamma_{ij} \ln p_{j} + \delta_{i} \left(\frac{x}{a(p)}\right)$$

$$+ \varphi_{i} x^{hc} + \sum_{n=1}^{n} \beta_{n} D + \mu_{i}$$

$$(4)$$

where  $w_i$  refers to the budget share of food category *i*, *p* is a vector of prices, *x* refers to the total per-capita food expenditure,  $x^{hc}$  is a vector of household characteristics and *D* is a set of regional dummies to capture differences in food expenditure. The price index, however, makes the specification of budget shares non-linear, which complicates its implementation in the mixed-integer linear programming used in MPMAS. Therefore, we transformed the price index into a linear approximation using a Stone price index. Transformation of the original AIDS model to Linear Approximation of Almost Ideal Demand System (LA-AIDS) using a Stone price index leads to the following linear specification of budget shares:

$$w_{i} = \alpha_{i} + \sum_{j=1}^{j} \gamma_{ij} \ln p_{j} + \delta_{i} \left( \frac{x}{\sum_{n=1}^{n} w_{n} \ln p_{n}} \right) + \varphi_{i} x^{hc} + \sum_{n=1}^{n} \beta_{n} D + \mu_{i}$$

$$(5)$$

The LA-AIDS model was then estimated using Zellner's Seemingly Unrelated Regression (SUR) technique, imposing the additional constraints of homogeneity, adding-up, and symmetry<sup>11</sup>.

In MPMAS, the complete household demand system was implemented through division of the underlying functions into a number of linear segments according to the size of the expenditure budget. The linear segments are included as decision variables in the agent MILP matrix and thereby allocate the available agent income to the various food and non-food items of the econometrically estimated AIDS. The income allocation is agent-specific and is defined by the amount of current income and by household size and household composition of a particular agent. In the after-harvest decision, agents in MPMAS can react to food shortages due to bad harvests or lower

<sup>&</sup>lt;sup>11</sup> Detailed estimation procedures as well as parameter estimates are included in section 2.8 of the appendix at the end of this chapter.

than planned cash inflows through various coping options. These coping options at the agent level include the purchase of additional food, consuming different less expensive or inferior food, and the selling of livestock. Among these agent coping strategies, reduced food intake and selling of livestock were implemented as last-resort decisions that households in the study area are typically reluctant to make. If disinvestment is insufficient to satisfy the individual food energy needs in MPMAS, the agents run into food energy deficits and starve.

## 2.3 Model validation

According to Box *et al.* (1987), "*Essentially, all models are wrong, but some are useful.*" This implies that in order to make simulation-based inferences about a system, the model should be submitted to a process of validation to ensure its usefulness. MPMAS, like other bioeconomic simulators, is at least partially validated, as it has been based on well-established models and equations used in agricultural economics and crop sciences. Moreover, the statistical relevance of all underlying mathematical functions, as well as the estimated parameters of agent production and consumption decisions, can be tested through econometric techniques (see the discussion in Schreinemachers and Berger, 2011).

Still, validation of results for the current application of MPMAS had to be achieved by conducting a goodness-of-fit test against available base year data. To this end, we regressed simulated agent data on observed data of 2006 with a zero intercept. A perfectly validated model would be indicated by a slope coefficient of one and an  $R^2$  of one (McCarl and Apland, 1986). To check the internal consistency of the simulation model, we tested the goodness-of-fit for four clusters of agents<sup>12</sup> (according to similarities in resource endowments) and for all agents aggregated. For this test we used one important indicator: the crop area shares selected by households. Table 2.1 shows the crop area shares at disaggregate cluster level. We found a close match between simulated and observed values as estimated parameter coefficients and  $R^2$  values are close to one, which made us believe that our model is useful in terms of simulating the correct processes.

<sup>&</sup>lt;sup>12</sup> Agents were divided into four clusters based on the number of agricultural plots operated by each household.

Table 2.1: Model validation results

Level	Slope coef	Std.err	R2
Micro(Clusters)	0.99	0.08	0.96
Cluster 0	0.98	0.05	0.98
Cluster 1	1.06	0.17	0.93
Cluster 2	0.95	0.05	0.98
Cluster 3	0.94	0.06	0.96

# 2.4 Results

In this section we present the results of our scenario-based analysis under current climatic and market conditions in Northern Ghana. A major challenge in our scenario design for the analysis of climate and price variability is the existence of a potentially large number of price, climate and policy intervention combinations (Claessens et al., 2012). In order to simulate the impacts of climate and price variability at the household level, we made use of re-sampling techniques and super-computing facilities. For capturing the single effect of climate variability, re-sampling was made based on time-series of temperature and rainfall data obtained from CPWF. For each repetition, a sequence of specific years was randomly drawn from our regional climate database, and crop yields were simulated with CROPWAT. The annual climate realization was then matched with a constant average price year. Similarly, for capturing the single effect of price variability, we used time-series of regional food crop prices, which were also provided by CPWF. These prices were converted into real terms and sequences of price years were then randomly drawn for each repetition and matched with a constant average climate year. Finally, in capturing the joint effects of climate and price variability, trajectories of given years were randomly drawn and the corresponding price and weather/crop yield values were used in each repetition. In doing so, we created 50 repetitions with 50 random weather trajectories, 50 repetitions with 50 random price years and 50 repetitions of random joint price and weather years<sup>13</sup>. In addition, for each repetition, we included credit and off-farm employment opportunities to capture the effects of policy interventions (Table 2.2).

<sup>&</sup>lt;sup>13</sup> Ideally, many repetitions would have produced a more precise estimate. However we choose 50 repetitions due to computational requirements. In this case for example, we conducted 454 simulation experiments with 1,600 agents over 15 years, which accounts to about 32.7 million mixed-integer LP problems solved. One simulation run took about 15 hours to complete on a Linux computer with 8 GByte RAM.

Scenario	Repetitions	Climate	Prices	Policy description
Baseline	1	constant	constant	Current intervention: absence of formal
				credit market and limited access to off-
				farm employment.
	1	constant	constant	Credit: access to credit at 25% interest
				rate, which have to be repaid within the
Baseline +				same cropping year.
policy	1	constant	constant	Off-farm: Improved off-farm employment
				opportunities
	1	constant	constant	credit + off-farm: credit along with
				improved access to off-farm employment
				opportunity
	50	variable	constant	Current intervention: absence of formal
				credit market and limited access to off-
Climate				farm employment.
variability only	50	variable	constant	Credit: access to credit at 25% interest
				rate, which have to be repaid within the
				same cropping year.
	50	variable	constant	Off-farm: Improved off-farm employment
				opportunities
	50	variable	constant	credit + off-farm: credit along with
				improved access to off-farm employment
<b>D</b>				opportunity
Price variability	50	constant	variable	Current intervention: absence of formal
only				credit market and limited access to off-
				farm employment.
Climate and	50	variable	variable	Current intervention: It assumes absence of
price variability				formal credit market and limited access to
				off-farm employment.
Climate and	50	variable	variable	Credit: access to credit at 25% interest
price variability				rate, which have to be repaid within the
+ policy	50			same cropping year.
	50	variable	variable	Off-farm: Improved off-farm employment
	50		11	opportunities.
	50	variable	variable	credit + off-farm: credit along with
				improved access to off-farm employment
				opportunity

Table 2.2: Scenarios analyzed to capture the effects of climate and price variability

In our simulation experiments, we used a constant average climate (and crop yields) together with constant average prices as a reference for comparing welfare changes under climate and price variability. Scenarios for credit and off-farm income were then designed to investigate the potential effects of policy interventions under climate and price variability. For the purpose of illustration, our results are divided into three subsections. The first sub-section presents baseline poverty and food security distributions without any climate and price variability<sup>14</sup>. Against these reference outcomes, we

<sup>&</sup>lt;sup>14</sup> We choose the baseline as a situation without any climate and price variability since a lack of an appropriate comparison unit may poses challenges for impact estimation. As a baseline, one can, for example, use the current levels of variability as a bench mark. However, without

present the results of climate and price variability effects in the second section. In the final sub-section, we address the effectiveness of policy interventions in the form of access to credit and off-farm opportunities.

#### 2.4.1 Baseline without climate and price variability

The baseline of our experiments is a hypothetical scenario constructed without any climate and price variability<sup>15</sup>, in which each individual agent is simulated recursively over a period of 15 years. Figure 2.2 shows the distribution of per-capita incomes under baseline conditions for each agent averaged over the simulation horizon. To highlight the share of poor agents, we included in this graph a vertical line at the international poverty line of US\$  $1.25^{16}$  per person and day.



Figure 2.2: Distribution of simulated per-capita income

In addition, we simulated the distribution of agent food security under constant climate and prices for two types of policy interventions. In these hypothetical scenarios, all households in MPMAS were given the option of borrowing short-term production

establishing how household income would have evolved without any climate variability, it is almost impossible to estimate the impact of climate variability on household income.

<sup>&</sup>lt;sup>15</sup> Baseline without any price and climate variability is constructed with no policy intervention options.

<sup>&</sup>lt;sup>16</sup> Note that the international poverty line of US\$ 1.25 per person per day is higher than the official poverty line used in Ghana<sup>-</sup>

credit at 25%<sup>17</sup> p.a. In analyzing the agent policy response, we used food energy consumption as an indicator for household food security. The food energy intake was quantified on a per-capita basis in male adult equivalents to control for differences in size and composition of households. The official poverty line for the study region is fixed at a welfare level of a person who meets 2,300 kilocalories per day per adult equivalent (GLSS, 2007). The simulation results show that access to improved credit and off-farm employment improves agent food security considerably (Figure 2.3). Moreover, the distribution of food energy consumption suggests that in particular the poorest agents would benefit from these policy interventions, as the left tail of the distribution was shifted and most poor households would cross the Ghanaian poverty line<sup>18</sup>.



Figure 2.3: Effectiveness of simulated policy interventions without variability

#### 2.4.2 Baseline with climate and price variability

With incomplete and inaccurate information about likely climatic conditions and selling prices in the upcoming growing season, most smallholder farmers in

<sup>&</sup>lt;sup>17</sup> The interest rate proposed by the government of Ghana for Micro finance institutions.

<sup>&</sup>lt;sup>18</sup> The SI conversion factor of one kilocalorie is 4.184 joule. Expressing the average annual energy requirement of an adult male (18-62 years old) in Ghana results in a poverty line of 3.259 GJ per capita and year.

developing countries make land use decisions that are optimized for "normal" average years, including some margin of flexibility and risk aversion. As a consequence, climate-related benefits cannot be fully exploited in years more favourable than average, while losses cannot be fully avoided in years more adverse than average. In addition, as there is a high correlation between weather and agricultural prices, climate variability usually goes together with price variability. However, since the poverty impacts of food price changes depend on the market position of each individual household (net sellers vs. net buyers), climate-induced food price variability can alter the relative income position of smallholder farmers (Mideksa, 2010). If the earning effects of higher food prices are larger than the mostly negative crop yield effects of climate variability, price variability might even offer opportunities to reduce poverty (Hertel and Rosch, 2010; Hertel *et al.*, 2010).

In disentangling the effects of climate and price variability, we analyzed hypothetical scenarios where agents were exposed to one type of variability alone, keeping the other factor constant. First, we kept prices constant and exposed agents to climate variability alone; then we kept climate and crop yields constant and exposed agents to price variability alone. Finally, we exposed households in MPMAS to climate and price variability simultaneously<sup>19</sup>. Our simulation results in Figure 2.4 suggest that climate variability alone has a pronounced negative effect on household income compared to the baseline without any variability. Impacts are especially felt at the poor end of the agent income distribution: with climate variability alone, the share of agents below the poverty line increases from 83% to 92%.

<sup>&</sup>lt;sup>19</sup> Note that while capturing the joint effect of climate and price variability, co-variation between price and climate is captured. Hence price variability was not modelled independent of climate variability.



Figure 2.4: Simulated effect of climate variability on agent income

Figure 2.5 further reveals the magnitudes of these effects by showing the differences in agent incomes compared to the hypothetical baseline without any variability. Over the full agent population, we found a negative effect of price variability alone, reducing the aggregate income of the agent population by about 7% on average. Since most agents are net food buyers as well as subsistence farmers producing mainly for own consumption, only a small proportion of agents were able to realize higher earnings from higher food prices. For climate variability alone, we found an even stronger negative effect: here the aggregate income of the agent population declined by slightly more than 8% on average compared to the baseline without any climate and price variability. Combining both types of variability in Figure 2.5, however, shows a pronounced adverse effect on agent incomes, which then declined by about 20% on average. The combined effect of climate and price variability is more severe than the individual effects because regional weather and agricultural prices are strongly correlated. In our regional dataset, unfavourable weather conditions were always accompanied by higher food prices. In this regard, both climate variability and price variability work in the same direction depending on the market position of households. We found a favourable effect for a small group of net food seller agents, where higher earnings from higher food prices compensated the adverse effects of climate variability. For the majority of net food buyers, however, joint climate and price variability leads to a serious decline in agent income.



Figure 2.5: Simulated effect of climate and price variability

Figure 2.6 reveals in more detail the heterogeneous impacts of joint climate and price variability at the individual agent level. One dot in the scatter plot represents the change of an individual agent's income averaged over 15 years compared to the income level of the same agent in the baseline without any variability. According to our simulations, income losses differ considerably in the agent population, but tend to be less severe among more affluent agents<sup>20</sup>.



Figure 2.6: Agent level effects of simulated price and climate variability

 $<sup>^{20}</sup>$  For the more affluent agents, income losses due to climate variability are compensated by gains through higher prices.

Figure 2.7 shows the role that livestock assets played for food security when agents cope with joint climate and price variability. The graph depicts the individual change of food consumption with increasing livestock herd sizes under joint variability of climate and prices. Although coping responses differ considerably among agents, we found that agents with more livestock tend to smooth consumption better than agents with smaller herd sizes.



Figure 2.7: Agent level livestock asset and simulated changes in food security

## 2.4.3 Assessment of potential policy interventions

Finally, we present the results of our agent-based policy analyses by examining the effects of providing improved access to credit and off-farm income opportunities under climate and price variability. Figure 2.8 shows the change in agent incomes with access to credit alone, and with both access to credit and off-farm employment opportunities.



Figure 2.8: Effectiveness of policy interventions under variability

In both cases, we found significant changes in income under climate and price variability for different policy responses. On average, agents who took credit could increase their income by 17% compared to those we did not take any credit. Furthermore, agents with credit and off-farm income opportunities could increase their income substantially. Moreover, as shown in Figure 2.9, policy interventions in the form of improved access to credit and off-farm income opportunities were found to be highly effective in improving the food security situation.



Figure 2.9: Agent level effects of improved credit and off-farm income

It was also necessary to capture in MPMAS the share of agents who fail to repay credit, which is an important policy indicator when considering the viability of improving access to credit as a policy intervention. In our simulation experiments, we found that due to climate and price variability, the overall default rate increased from about 7% to 19%. In MPMAS, agents were only allowed to take short-term credit tied to production expenses. Generally, agent decisions in MPMAS are constrained to paying back their short-term credit and agents cannot plan to default on credit. Still, in cases where agents face severe food shortages that cannot be compensated even by selling livestock, they must default on credit. This currently has no consequence in MPMAS, as they can take up credit again in next period. In the next chapter, we included a more detailed treatment of credit default.

# 2.5 Discussion

One advantage of agent-based simulation over conventional bioeconomic modelling is its ability to capture full heterogeneity and interaction of smallholder households in their ability to cope with climate and price variability. Studies by Dercon and Christiaensen (2011) and Ziervogel et al. (2006) suggest that current adaptation measures are not likely to be equally effective as households differ in terms of income, resource endowments and adaptation capacity. As a consequence, adaptation policies designed based on the "representative farm" are of limited use when searching for targeted pro-poor policies in which agent to agent interaction is important (Berger et al., 2006). By applying an agent-based modelling approach, we analyzed the highly relevant empirical questions as to whether the effects of climate and price variability are distributed uniformly and to which extent policy interventions for improved credit and off-farm employment could reach all households. We ranked agents based on their baseline incomes without any variability in climate and prices and computed in all variability and policy scenarios the individual change in income and food consumption in reference to this baseline. Our simulation results suggest that even though climate and price variability have a negative effect, the effect is more pronounced for poor agent households compared to better-off agents. These results are in line with similar studies in SSA pointing out that poor farm households are more vulnerable to climate variability due to their reliance on climate sensitive activities and inability to cope with shocks (Knox et al., 2012; Thornton et al., 2009; Hertel et al., 2010).

According to Pandey *et al.* (2007); Lobell et *al.* (2008); and Dercon and Christiaensen (2011), most farm households in developing countries undertake both ex-ante and expost strategies to combat the negative effects of climate and price variability. These include, among others, selling livestock as a means of smoothing consumption over time. We considered this and other coping strategies in our agent-based model and thereby analyzed the importance of livestock wealth as a buffer against variability-induced consumption shocks. In our simulation experiments, we found that current climate and price fluctuations affect consumption security at the agent level, but to a smaller extent for those agents with larger livestock holdings.

It has been well documented that smallholder households in Northern Ghana lack adequate access to credit in order to finance on-farm productivity gains (Yilma *et al.*, 2008). Moreover, the absence of credit markets forces households to engage in costly adaptation strategies that aggravate poverty and food insecurity, such as the selling of livestock. Studies also indicated that in addition to providing short-term production credit, the promotion of non-farm employment opportunities plays a crucial role in enhancing food security under climate variability for poor rural farm households (Barrett *et al.*, 2001). The role of off-farm employment is even more important in light of climate variability, as households face seasonal food shortages resulting from low productivity (Owusu *et al.*, 2011).

Proper policy interventions in the form of credit and livelihood diversification through off-farm income opportunities can therefore play a significant role in the reduction of poverty under climate and price variability today and in the future. Our simulation results are in line with studies by Owusu *et al.* (2011), who found that off-farm income has positive and significant effects on household food security in Northern Ghana. If well-targeted credit and off-farm income generating activities are in place, the food security situation of farm households can be improved substantially. Still, the opportunities for off-farm employment are very limited in areas like Northern Ghana where agriculture is the predominant economic activity. In this simulation study, we assumed that agents obtain off-farm jobs at fixed current wages once they decide to participate in the off-farm job market. In the absence of more detailed labour market data, we implemented a simple upper bound for off-farm employment at the individual agent level, without considering a possible decline in jobs and wages under climate

variability. As a result, the findings might overestimate the potential of off-farm income as a means of livelihood diversification.

## 2.6 Conclusions

This paper investigates the effects of current climate and price variability on smallholder agriculture in Northern Ghana with a focus on household-level adaptation strategies and policy interventions, especially those related to improved credit and off-farm income opportunities. We employed a micro-simulation approach driven by regional climate and price data for assessing the impacts of their variability at household level. In particular, we used the agent-based simulation package MPMAS to address the special challenges of climate variability in the context of small-scale and semi-subsistence agriculture, capturing non-separable production and consumption decisions as well as the role of livestock for consumption smoothing. To ensure reliability and usefulness of results, our model approach was validated with reference to food security, land use and overall poverty levels based on observed survey values.

Like any other model of climate variability, our simulation approach faces some limitations. Due to the lack of adequate empirical data, we only implemented the most important individual agent-coping strategies of smallholders in Northern Ghana, but did not consider local safety nets and kinship ties explicitly. Regardless of these limitations, the methodology presented in this study shows how outputs from climate research can be translated into income and food security equivalents. In addition, the study provides insights into the role of household adaptation and policy intervention in order to improve the livelihoods of smallholder farmers in the face of increasing climate variability. The software package is ready for coupling with dynamically downscaled climate models and can be used for detailed regional impact assessments of future climate conditions.

In the literature, it has been suggested that income sources that are less sensitive to climate variability should be advocated in order to enhance household welfare in the long run (Mideksa, 2010). Policy interventions of this type include measures to reduce reliance on rain-fed agriculture through the transformation of production systems. Here we argue that given the limited importance of irrigation agriculture in Northern Ghana this might not be the only way out. Instead, policy interventions that boost production

while including an element of diversification of income sources should be investigated in more detail. Our argument is supported by the simulation outcomes of our improved credit and off-farm employment interventions, which helped to mitigate the negative effects of climate and price variability. More empirical research is needed, however, to find new ways of implementing effective smallholder credit schemes in Northern Ghana.

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#### 2.8 Appendix

#### Detailed description of agent consumption behaviour in MPMAS-Ghana

Capturing consumption behaviour is an essential step in the analysis of welfare changes emanating from climate and price variability. The point of departure in capturing climate induced consumption vulnerabilities starts from the standard economic relationship between savings and income (i.e., total income (Y) is equal to the sum of savings (S) and total expenditure (TE)):

$$Y = S + TE$$

For a given household, savings is specified as a function of income and other household specific characteristics affecting savings levels. For this study, the following quadratic specification of the savings function is used:

$$S = \alpha_0 + \beta_1 Y + \beta_2 Y^2 + \beta_3 x^{hc} + \sum_{n=1}^n \beta_n D + \mu_i$$

Where S is total savings from a given level of income, Y is the total disposable income,  $x^{hc}$  includes household characteristics such as household size and D is a vector of regional dummies, capturing differences in climate and agro-ecology. An alternative form of the savings function is the logarithmic specification. The quadratic specification was opted for over the logarithmic specification because it enables capturing the possibility of negative savings (dis-savings), which the logarithmic specification does not allow for. Negative savings implies that income is not enough to cover expenditure, requiring households to use other options, such as selling livestock, taking consumption credit, etc., to fulfil their consumption requirements. This is especially important in the case of food-insecure households in Ghana, where dissavings are quite common. Parameterization of the quadratic savings function was completed using income and expenditure data from the GLSS5 data set.

$\begin{array}{cccccccccccccccccccccccccccccccccccc$		Savings	Total expenditure
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Income	0.319***	0.681***
$\begin{array}{llllllllllllllllllllllllllllllllllll$		(0.044)	(0.044)
Household size $(0.00007)$ $(0.00007)$ Household size $-8.74^{***}$ $8.74^{***}$ $(0.378)$ $(0.378)$ $(0.378)$ Western $-190.79^{***}$ $190.79^{***}$ $(8.55)$ $(8.55)$ $(8.55)$ Central $-108.0^{***}$ $108.0^{***}$ $(6.43)$ $(6.43)$ $(6.43)$ Greater Accra $-260.68^{***}$ $260.68^{***}$ $(11.09)$ $(11.09)$ $(11.09)$ Volta $-116.28^{***}$ $116.28^{***}$ $(7.31)$ $(7.31)$ $(7.31)$ Eastern $-132.76^{***}$ $132.76^{***}$ $(7.22)$ $(7.22)$ $(7.22)$ Ashanti $-171.0^{***}$ $110.81^{***}$ $(7.29)$ $(7.29)$ $(7.29)$ BrongAhafo $-110.81^{***}$ $110.81^{***}$ $(7.58)$ $(7.58)$ $(7.58)$ Upper west $-13.62^{***}$ $45.77^{***}$ $(5.55)$ $(5.55)$ $(5.55)$ Constant $-41.2^{***}$ $41.2^{***}$ $(8.11)$ $(8.11)$ $(8.11)$ N $5748$ $1225$ $R^2$ $0.296$ $Prob > F$ $0.000$ $=$	Income-squared	0.00025***	-0.00025***
Household size $-8.74^{***}$ $8.74^{***}$ Western $-190.79^{***}$ $190.79^{***}$ $-190.79^{***}$ $190.79^{***}$ Central $-108.0^{***}$ $108.0^{***}$ Greater Accra $-260.68^{***}$ $260.68^{***}$ Greater Accra $-260.68^{***}$ $260.68^{***}$ Volta $-116.28^{****}$ $116.28^{***}$ $(7.31)$ $(7.31)$ $(7.31)$ Eastern $-132.76^{***}$ $132.76^{***}$ $(7.22)$ $(7.22)$ $(7.29)$ BrongAhafo $-110.81^{***}$ $110.81^{***}$ $(7.72)$ $(7.58)$ $(7.58)$ Upper west $-13.62^{****}$ $13.62^{****}$ $(9.64)$ $(9.64)$ $(9.64)$ Rural $89.86^{***}$ $-89.86^{***}$ $(5.55)$ $(5.55)$ $(5.55)$ Constant $41.2^{***}$ $41.2^{***}$ $(8.11)$ $(8.11)$ $(8.11)$ N $5748$ $1225$ Prob> F $0.0000$ $-80.80$	-	(0.00007)	(0.00007)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Household size	-8.74***	8.74***
Western $-190.79^{***}$ $190.79^{***}$ Central $(8.55)$ $(8.55)$ Central $-108.0^{***}$ $108.0^{***}$ Greater Accra $(6.43)$ $(6.43)$ Greater Accra $-260.68^{***}$ $260.68^{***}$ $(11.09)$ $(11.09)$ $(11.09)$ Volta $-116.28^{***}$ $116.28^{***}$ $(7.31)$ $(7.31)$ $(7.31)$ Eastern $-132.76^{***}$ $132.76^{**}$ $(7.22)$ $(7.22)$ $(7.29)$ Ashanti $-171.0^{***}$ $171.0^{***}$ $(7.29)$ $(7.29)^{***}$ $(7.29)^{***}$ BrongAhafo $-110.81^{***}$ $110.81^{***}$ $(7.71)$ $(7.71)$ $(7.71)$ Northern $-45.77^{***}$ $45.77^{***}$ $(9.64)$ $(9.64)$ $(9.64)$ Rural $89.86^{***}$ $-89.86^{***}$ $(5.55)$ $(5.55)$ $(5.55)$ Constant $-41.2^{***}$ $41.2^{**}$ $R^2$ $0.296$ $1225$ Prob> F $0.0000$ $-100.12^{***}$		(0.378)	(0.378)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Western	-190.79***	190.79***
$\begin{array}{cccc} {\rm Central} & -108.0^{***} & 108.0^{***} \\ & (6.43) & (6.43) \\ {\rm Greater Accra} & -260.68^{***} & 260.68^{***} \\ & (11.09) & (11.09) \\ {\rm Volta} & (11.09) & (11.09) \\ {\rm Volta} & -116.28^{***} & 116.28^{***} \\ & (7.31) & (7.31) \\ {\rm Eastern} & -132.76^{***} & 132.76^{***} \\ & (7.22) & (7.22) \\ {\rm Ashanti} & -171.0^{***} & 171.0^{***} \\ & (7.29) & (7.29) \\ {\rm BrongAhafo} & -110.81^{****} & 110.81^{****} \\ & (7.71) & (7.71) \\ {\rm Northern} & -45.77^{***} & 45.77^{***} \\ & (7.58) & (7.58) \\ {\rm Upper west} & -13.62^{***} & 13.62^{***} \\ & (9.64) & (9.64) \\ {\rm Rural} & 89.86^{***} & -89.86^{***} \\ & (5.55) & (5.55) \\ {\rm Constant} & -41.2^{***} & 41.2^{***} \\ & (8.11) & (8.11) \\ \hline {\rm N} \\ {\rm R}^2 \\ {\rm Prob>F} & 0.0000 \\ \end{array}$		(8.55)	(8.55)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Central	-108.0***	108.0***
$\begin{array}{llllllllllllllllllllllllllllllllllll$		(6.43)	(6.43)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Greater Accra	-260.68****	260.68***
Volta $-116.28^{***}$ $116.28^{***}$ Eastern $(7.31)$ $(7.31)$ Eastern $-132.76^{***}$ $132.76^{***}$ Ashanti $(7.22)$ $(7.22)$ Ashanti $-171.0^{***}$ $171.0^{***}$ $(7.29)$ $(7.29)$ $(7.29)$ BrongAhafo $-110.81^{***}$ $110.81^{***}$ $(7.71)$ $(7.71)$ $(7.71)$ Northern $-45.77^{***}$ $45.77^{***}$ $(7.58)$ $(7.58)$ $(7.58)$ Upper west $-13.62^{***}$ $13.62^{***}$ $(9.64)$ $(9.64)$ $(9.64)$ Rural $89.86^{***}$ $-89.86^{***}$ $(5.55)$ $(5.55)$ $(5.55)$ Constant $-41.2^{***}$ $41.2^{***}$ $(8.11)$ $(8.11)$ $(8.11)$ N $5748$ $1225$ $R^2$ $0.296$ $-125$ Prob> F $0.0000$ $-116.28^{***}$		(11.09)	(11.09)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Volta	-116.28***	116.28***
Eastern $-132.76^{***}$ $132.76^{***}$ Ashanti $(7.22)$ $(7.22)$ Ashanti $-171.0^{***}$ $171.0^{***}$ $(7.29)$ $(7.29)$ $(7.29)$ BrongAhafo $-110.81^{***}$ $110.81^{***}$ $(7.71)$ $(7.71)$ $(7.71)$ Northern $-45.77^{***}$ $45.77^{***}$ $(7.58)$ $(7.58)$ $(7.58)$ Upper west $-13.62^{***}$ $13.62^{***}$ $(9.64)$ $(9.64)$ $(9.64)$ Rural $89.86^{***}$ $-89.86^{***}$ $(5.55)$ $(5.55)$ $(5.55)$ Constant $-41.2^{***}$ $41.2^{***}$ $(8.11)$ $(8.11)$ $(8.11)$ N $5748$ $1225$ Prob> F $0.0000$ $(5.55)$		(7.31)	(7.31)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Eastern	-132.76***	132.76***
$\begin{array}{llllllllllllllllllllllllllllllllllll$		(7.22)	(7.22)
$\begin{array}{cccc} (7.29) & (7.29) \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & & \\ & & & \\ & & & & \\ $	Ashanti	-171.0***	171.0***
$\begin{array}{cccc} BrongAhafo & -110.81^{***} & 110.81^{***} \\ & (7.71) & (7.71) \\ Northern & -45.77^{***} & 45.77^{***} \\ & (7.58) & (7.58) \\ Upper west & -13.62^{***} & 13.62^{***} \\ & (9.64) & (9.64) \\ Rural & 89.86^{***} & -89.86^{***} \\ & (5.55) & (5.55) \\ Constant & -41.2^{***} & 41.2^{***} \\ & (8.11) & (8.11) \\ N & 5748 & 1225 \\ R^2 & 0.296 \\ Prob> F & 0.0000 \\ \end{array}$		(7.29)	(7.29)
$\begin{array}{cccc} (7.71) & (7.71) \\ -45.77^{**} & 45.77^{**} \\ (7.58) & (7.58) \\ \\ Upper west & -13.62^{***} & 13.62^{***} \\ (9.64) & (9.64) \\ \\ Rural & 89.86^{***} & -89.86^{***} \\ (5.55) & (5.55) \\ \\ Constant & (8.11) & (8.11) \\ \\ N & 5748 & 1225 \\ R^2 & 0.296 \\ \\ Prob> F & 0.0000 \\ \end{array}$	BrongAhafo	-110.81***	110.81***
Northern $-45.77^{***}$ $45.77^{***}$ Upper west $(7.58)$ $(7.58)$ Upper west $-13.62^{***}$ $13.62^{***}$ $(9.64)$ $(9.64)$ $(9.64)$ Rural $89.86^{***}$ $-89.86^{***}$ Constant $(5.55)$ $(5.55)$ Constant $-41.2^{***}$ $41.2^{***}$ $(8.11)$ $(8.11)$ N $5748$ $1225$ R <sup>2</sup> $0.296$ $0.0000$		(7.71)	(7.71)
$\begin{array}{cccc} (7.58) & (7.58) \\ -13.62^{***} & 13.62^{***} \\ (9.64) & (9.64) \\ \text{Rural} & 89.86^{***} & -89.86^{***} \\ (5.55) & (5.55) \\ \text{Constant} & -41.2^{***} & 41.2^{***} \\ & (8.11) & (8.11) \\ \hline N & 5748 & 1225 \\ R^2 & 0.296 \\ \text{Prob> F} & 0.0000 \\ \end{array}$	Northern	-45.77***	45.77***
Upper west $-13.62^{***}$ $13.62^{***}$ Rural(9.64)(9.64)Rural $89.86^{***}$ $-89.86^{***}$ (5.55)(5.55)(5.55)Constant $-41.2^{***}$ $41.2^{***}$ (8.11)(8.11)(8.11)N57481225R <sup>2</sup> 0.2960.0000		(7.58)	(7.58)
Rural $(9.64)$ $(9.64)$ Rural $89.86^{***}$ $-89.86^{***}$ $(5.55)$ $(5.55)$ Constant $-41.2^{***}$ $41.2^{***}$ $(8.11)$ $(8.11)$ N $5748$ $1225$ $R^2$ $0.296$ Prob> F $0.0000$	Upper west	-13.62***	13.62***
Rural $89.86^{***}$ $-89.86^{***}$ Constant $(5.55)$ $(5.55)$ Constant $-41.2^{***}$ $41.2^{***}$ $(8.11)$ $(8.11)$ N $5748$ $1225$ R <sup>2</sup> $0.296$ $0.0000$		(9.64)	(9.64)
$\begin{array}{cccc} (5.55) & (5.55) \\ -41.2^{***} & 41.2^{***} \\ \hline (8.11) & (8.11) \\ \hline N & 5748 & 1225 \\ R^2 & 0.296 \\ Prob> F & 0.0000 \\ \end{array}$	Rural	89.86***	-89.86***
Constant $-41.2^{***}$ $41.2^{***}$ (8.11)(8.11)N5748R <sup>2</sup> 0.296Prob> F0.0000		(5.55)	(5.55)
$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$	Constant	-41.2***	41.2***
		(8.11)	(8.11)
R <sup>2</sup> 0.296           Prob> F         0.0000	N	5748	1225
Prob> F 0.0000	$R^2$	0.296	
de d	Prob> F	0.0000	

Table 2.3: Regression estimates for the saving and expenditure models

Robust standard errors in parentheses, p < 0.05, p < 0.01, p < 0.001

The second stage, where household agents allocate expenditure between food and nonfood items, is captured using a modified version of the Working-Leser model, following Schreinemachers *et al.* (2007). In this decision, agents allocate income aftersavings into food and non-food expenditures. In countries like Ghana, where food security is a critical question, food expenditure values are instrumental as policy indicators for quantifying poverty and food security. The Working-Leser specification considers commodity budget shares as a function of the logarithm of per-capita expenditure. For this study, the modified version of the Working-Leser model is specified as follows:

$$\omega_{i} = \alpha_{0} + \beta_{1} \ln(PCE) + \beta_{2} x^{hc} + \sum_{n=1}^{n} \beta_{n} D + \mu_{i}$$
(6).

where  $\omega_i$  is the share of food expenditure from the total expenditure, *PCE* is per capita expenditure,  $x^{hc}$  are household and demographic variables and *D* is a vector of regional dummies. The Working-Leser model was estimated using GLSS5 data on expenditure, in which information on different sources of income and food and non-food expenditures were recorded. Household's food consumption is comprised of monetary expenditures on food, quantity of consumption from own harvest, and gifts. The quantity of own consumption was converted into imputed values using the community level price information of food items.

	Food	Non-food
ln( per capita expenditures)	-0.0093***	0.0093***
	(0.003)	(0.003)
Household size	-0.0024***	$0.0024^{***}$
	(0.0002)	(0.0002)
Western	-0.046****	$0.046^{***}$
	(0.0097)	(0.0097)
Central	-0.018***	0.018**
	(0.009)	(0.009)
Greater Accra	-0.045***	$0.045^{***}$
	(0.0098)	(0.0098)
Volta	-0.053****	$0.053^{***}$
	(0.0089)	(0.0089)
Eastern	-0.051****	$0.051^{***}$
	(0.009)	(0.009)
Ashanti	-0.0499***	$0.0499^{***}$
	(0.0088)	(0.0088)
BrongAhafo	-0.0046	0.0046
	(0.009)	(0.009)
Northern	-0.0067	0.0067
	(0.01)	(0.01)
Upper west	-0.063***	0.063****
	(0.0116)	(0.0116)
Rural	0.032***	-0.032****
	(0.0042)	(0.0042)
Constant	$0.667^{***}$	0.333****
	(0.016)	(0.016)
N	5837	1225
$\mathbf{R}^2$	0.153	
Prob> F	0.0000	
		0.001

Table 2.4: Regression estimates for the food and non-food expenditure models

Robust standard errors in parentheses, p < 0.05, p < 0.01, p < 0.01

In the final stage, where agents allocate food expenditure to specific food items is parameterized using the AIDS model. The AIDS model is chosen as it satisfies the axioms of rational choice and allows for the consistent aggregation of individual demand curves to a market demand curve (Deaton and Muellbauer, 1980). Different variants of the AIDS model have been applied for the estimation of consumer behaviour in developing countries. Ecker and Qaim (2008) and Nigussie and Shahidur (2012), for example, used the quadratic version of AIDS (QUAIDS) for the analysis of consumer behaviour in Malawi and Ethiopia respectively. Another popular version of the AIDS model is its linear approximation, the Linear Approximate of Almost Ideal Demand System (LA/AIDS). In all of the specifications, the budget share equation for each food category is specified as a function of its own price, the price of other goods in the demands system and the real total expenditure on the group of food items. Specifically the model is presented as follows:

$$\omega_{i} = w_{i} = \alpha_{0} + \sum_{j=1}^{j} \gamma_{ij} \ln p_{j} + \delta_{i} \left(\frac{x}{a(p)}\right) + \varphi_{i} x^{hc} + \sum_{n=1}^{n} \beta_{n} D + \mu_{i}$$

$$(7)$$

where  $w_i$  refers to the budget share of food category *i*, *p* is a vector of prices, *x* refers to the total per-capita food expenditure,  $x^{hc}$  is a vector of household characteristics and *D* is a set of regional dummies. In the original AIDS model of Deaton and Muellbauer (1980), the price index a(p) is given as:

$$\omega_{i} = lna(p) = \alpha_{0} + \sum_{n=1}^{n} \alpha_{n} lnp_{n} + \frac{1}{2} \sum_{j=1}^{j} \sum_{n=1}^{n} lnp_{j} lnp_{n}$$
(8).

This price index, however, makes the specification of budget shares non-linear, which complicates its implementation in mixed-integer linear programming (MILP) as used in MPMAS. Therefore we transformed the price index into a linear approximation using a Stone price index, calculated as:

$$a(p) = \sum_{n=1}^{n} w_n ln p_n \tag{9}$$

Transformation of the original AIDS model using a Stone price index leads to the following linear specification of budget shares:

$$w_{i} = \alpha_{i} + \sum_{j=1}^{J} \gamma_{ij} \ln p_{j} + \delta_{i} \left( \frac{x}{\sum_{n=1}^{n} w_{n} \ln p_{n}} \right) + \varphi_{i} x^{hc} + \sum_{n=1}^{n} \beta_{n} D + \mu_{i}$$

$$(10).$$

Consistent estimation of the above demand system, however, requires controlling for selection bias, as households may not consume all food items during the survey period. Selection bias due to zero consumption complicates the estimation procedure, as unit values on prices cannot be derived from expenditure data (Schreinemachers *et al.* 2007). We therefore computed the proportion of zero consumption for each food category from the survey data to examine the severity of this problem. In most of the cases, we found a rather high proportion of zero consumption and, as a consequence, implemented Heckman's two-step estimation procedure for controlling selection bias. In the first step, the probability that a given household consumes a given food item; in the second step, these inverse Mills ratios were used as a correcting variable in the estimation. Following Chern *et al.* (2003), the first step regression of Heckman's two-step estimation procedure is specified as:

$$pr(w_i > 0) = \alpha_0 + \sum_{j=1}^{j} \gamma_{ij} \ln p_j + \delta_i \left(\frac{x}{a(p)}\right) + \varphi_i x^{hc} + \sum_{n=1}^{n} \beta_n D + \mu_i \quad (11).$$

From the above regression, the inverse Mills ratio (IMR) is computed as:

$$IMR = \frac{\varphi(p, y, x^{hc}, D)}{\vartheta(p, y, x^{hc}, D)}$$
(12)

where  $\varphi$  refers to the density probability function and  $\vartheta$  refers to the cumulative probability function. The estimation in the second step is then specified as:

$$w_{i} = \alpha_{0} + \sum_{j=1}^{j} \gamma_{ij} \ln p_{j} + \delta_{i} \left(\frac{x}{a(p)}\right)$$

$$+ \varphi_{i} x^{hc} + \rho_{i} IMR + \sum_{n=1}^{n} \beta_{n} D + \mu_{i}$$
(13).

The complete demand system for LA/AIDS was then estimated using Zellner's Seemingly Unrelated Regression (SUR) technique, imposing the additional constraints of homogeneity, adding-up, and symmetry.

	Staple	Legumes	Meat &	Fruits &	Fish	Necessities
			Poultry	vegetables		
ln(Staple)	-0.0158***	0.009***	0.0012***	0.00117	0.0027***	0.005***
· • ·	(0.0028)	(0.00096)	(0.0012)	(0.0018)	(0.001)	(0.0009)
ln(Legumes)	$0.0089^{***}$	-0.005***	-0.0012**	-0.0032***	0.00015	-0.00087*
	(0.0096)	(0.0008)	(0.0005)	(0.0009)	(0.0006)	(0.0005)
ln(Meat &Poultry)	-0.0036 <sup>***</sup>	-0.0012 <sup>*</sup>	$0.0167^{***}$	-0.0015	0.000004	-0.0007
(	(0.0013)	(0.0005)	(0.0009)	(0.00098)	(0.0005)	(0.00049)
In(Fruit and Vegetables)	0.0012	-0.0032***	-0.0014	0.00027***	-0.0036***	0.0024***
m(11ate and + egetaeres)	(0.0018)	(0,0009)	(0,0009)	(0.0022)	(0,0009)	(0,0009)
ln(Necessities)	$0.0027^{***}$	0.00016	0.000004	-0.0036***	-0.00046**	-0.0021***
m(recession)	(0,001)	(0,00010)	(0.0055)	(0,0009)	(0,0008)	(0.00021)
ln(fish)	0.005***	-0.0009*	-0.0007	(0.0007)	$-0.0021^{***}$	-0.0085***
m(msn)	(0,000)	(0.00053)	(0.0007)	(0.0024)	(0,0006)	(0.0005)
ln(Luvuriag)	(0.0007)	(0.00055)	(0.000+7)	(0.0007)	(0.0000)	0.0048***
III(Luxuries)	(0.0013)	(0.0012)	(0.0023)	(0.0044)	(0.0034)	(0.0048)
ln (avn an ditura)/stans	(0.0011)	(0.00040)	(0.00078)	(0.00089)	(0.0003)	(0.00043)
in(expenditure)/stone	-0.003	(0.003)	(0.011)	-0.023	-0.0034	-0.003
Household size	(0.0022)	(0.0009)	(0.0013)	(0.0010)	(0.0009)	(0.0007)
Household size	0.00047	0.0004	0.0003	-0.00135	-0.00035	-0.00032
	(0.0002)	(0.0001)	(0.00015)	(0.0002)	(0.00009)	(0.00009)
Nonelection hazard	-0.134	-0.0035	-0.0344	0.027	-0.082	-0.0398
	(0.0139)	(0.0058)	(0.005)	(0.017)	(0.009)	(0.0125)
Western	0.118	-0.152	-0.0138	0.184	-0.0058	-0.041
	(0.0139)	(0.0035)	(0.005)	(0.008)	(0.0037)	(0.0032)
Central	0.093	-0.147	-0.029	0.206	0.025	-0.038
	(0.0094)	(0.003)	(0.005)	(0.008)	(0.0036)	(0.0031)
Greater Accra	0.087	0.148	-0.018	0.164	-0.0032	-0.040
	(0.010)	(0.0036)	(0.0051)	(0.0085)	(0.0038)	(0.0033)
Volta	0.048	0.136	-0.013	0.179***	0.009**	-0.017
	(0.0095)	(0.0034)	(0.005)	(0.0083)	(0.0036)	(0.0031)
Eastern	$0.095^{***}$	$0.144^{***}$	-0.0122**	$0.181^{***}$	-0.0028	-0.036***
	(0.0092)	(0.0032)	(0.0049)	(0.0079)	(0.0036)	(0.003)
Ashanti	$0.124^{***}$	-0.154***	-0.00002	$0.160^{***}$	$-0.0058^{*}$	-0.038***
	(0.009)	(0.0034)	(0.0049)	(0.0076)	(0.0035)	(0.0031)
BrongAhafo	$0.122^{***}$	$-0.150^{***}$	-0.0015	$0.142^{***}$	$0.0081^{**}$	-0.0364***
	(0.0098)	(0.0035)	(0.005)	(0.008)	(0.0037)	(0.003)
Northern	$0.102^{***}$	$-0.078^{***}$	0.0044	$0.025^{***}$	0.0019	-0.004
	(0.0104)	(0.0036)	(0.0056)	(0.0074)	(0.004)	(0.0034)
Upper west	0.083***	-0.113***	0.0045	-0.0006	-0.0018***	-0.015***
••	(0.015)	(0.0052)	(0.008)	(0.011)	(0.0057)	(0.0049)
Rural	0.011***	$0.007^{***}$	-0.021 ***	0.024***	-0.0062***	-0.002
	(0.004)	(0.0014)	(0.002)	(0.0029)	(0.0016)	(0.0014)
Constant	0.368***	0.138 <sup>***</sup>	0.0.735***	0.116 <sup>***</sup>	0.146***	0.132***
	(0.0146)	(0.0067)	(0.0102)	(0.012)	(0.0059)	(0.005)
N	5958	5958	5958	5958	5958	5958
$\mathbb{R}^2$	0.097	0.405	0.214	0.214	0.085	0.15
	*	**	***		0.000	0.10

Table 2.5: Regression estimates for the LA/AIDS model

Standard errors in parentheses, p < 0.05, p < 0.01, p < 0.001

As described above, we grouped food items into seven broad categories: staples, legumes, meat and poultry, fruit and vegetables, fish, necessities and other food categories. Table 2.6 shows budget shares, weighted average prices, and uncompensated own and expenditure elasticities computed for each food category.

Food category	Own price	Expenditure	Budget shares
	elasticity	elasticity	
Staple	-0.57	0.99	0.463
Legumes	-1.06	1.11	0.046
Meat &Poultry	-0.70	1.15	0.073
Fish	-0.82	0.86	0.177
Vegetables and fruits	-0.91	0.94	0.097
Necessities	-1.05	0.93	0.069
Luxuries	-1.10	1.33	0.075

Table 2.6: Elasticity estimates and budget shares

#### Capturing crop-specific climate variability effects with CROPWAT

The crop yields were modelled following the FAO56 approach (Clarke *et al.*, 1998, Smith, 1992). The crop-water requirement (*CWR*) for crop c in month m is the product of a crop coefficient (*Kc*), the potential evapotranspiration (*ETO*), and the planted area (*Area*):

$$CWR_{cm} = Kc_{cm} * ETO_m * Area_{cm}$$
(14)

The *CWR* could either be met through irrigation (*IRR*) or rainfall, which was converted into effective rainfall (*ER*) to capture the share of rainfall actually available to the crop, depending on its growth stage. The amount of water actually supplied (*CWS*) was then as follows:

$$CWS_{cm} = ER_{cm} + IRR_{cm}$$
(15)

For lack of detailed irrigation response data from the study region, the quotient of crop water supplied and the crop water requirement were simply averaged over all months with non-zero crop water requirements:

$$Kr_c = (1/m * \sum (CWS_{cm} / CWR_{cm}) | CWR_{cm} > 0)$$
(16)

The crop growth model assumed that the crop yield was lost if the average Kr fell below 0.5, while for Kr values greater than or equal to 0.5 the Kr value was multiplied by the crop yield potential (*YPOT*) to simulate the actual crop yield ( $Y_c$ ):

$$Y_{c} = \begin{cases} Kr_{c} * YPOT_{c} & \text{if } Kr_{c} \geq 0.5 \\ 0 & \text{if } Kr_{c} < 0.5 \end{cases}$$
(17)

The main source of irrigation water in the Upper East Region is surface water and rainfall, which were simulated with the distributed hydrology model WASIM-ETH. The two large-scale irrigation projects (Tono and Vea), 88 small dams and river water pumping at the White Volta River are the source of surface water supply. The available irrigation water in each irrigation site (inflow) is then shared among the model agents based on their amounts of irrigable land in that particular irrigation site.

# 3 Can small holder farmers adapt to climate variability, and how effective are policy interventions? Micro-simulation results for Ethiopia.

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#### Abstract

Climate variability with unexpected droughts and floods causes serious production losses and worsens food security, especially in Sub-Saharan Africa. This study applies stochastic modeling to analyze smallholder adaptation to climate and price variability in Ethiopia. It uses the agent-based simulation package MPMAS to capture nonseparable production and consumption decisions at household level, considering livestock and eucalyptus sales for consumption smoothing, as well as farmer response to policy interventions. We find the promotion of new maize and wheat varieties to be an effective adaptation option, on average, especially when accompanied by policy interventions such as credit and fertilizer subsidy. We also find that the effectiveness of available adaptation options is quite different across the heterogeneous smallholder population in Ethiopia. This implies that policy assessments based on average farm households may mislead policy makers to adhere to interventions which are beneficial on average albeit ineffective in addressing the particular needs of poor and food insecure farmers.

JEL classification: C61, Q54, C63, Q12, D12

Keywords: mixed rain-fed agriculture, coping with uncertainty, farm-level modeling, multi-agent systems, OpenMPI

### 3.1 Introduction

Ethiopia is highly exposed to climate variability, as agriculture forms the basis of the economy contributing roughly 43% to GDP, 90% of export earnings and 80% of employment (MoFed, 2010). Moreover, agriculture is predominately rain-fed with limited irrigation coverage, which means that shifts in the timing and amount of rainfall impinge on agricultural production and food security (Di Falco and Chavas, 2009; Di Falco et al., 2014). Smallholder farmers cultivating about 95% of the total crop area and producing more than 90% of Ethiopia's agricultural output are found to be the most affected by climate variability and climate change (Block et al., 2008; Deressa et al., 2009; Arndt et al., 2011; Di Falco et al., 2011; Milman and Arsano, 2013; Di Falco and Veronesi, 2014).

Disentangling the effects of climate variability from other determinants of agricultural production and food security is crucial not only to design appropriate climate mitigation and adaptation policies, but also to prioritize policy interventions. One of these other determinants of food security deserving special attention is price variability. The effect of price variability on household food security depends on the rate and speed of productivity-induced changes of market prices, the market position of households (net buyer vs. net seller), the extent of market integration of farm households, as well as changes in wages. In line with this, Hertel et al. (2010), Mideksa (2010) and Robinson et al. (2012) argued that analyzing only the production effects of climate variability without considering the effects of inherent market forces through price changes would underestimate the effects of climate variability. Antle et al. (2014), in addition, stressed the importance of population-based simulation of technology adoption.

Against this background, we make use of computer simulation in this paper to address two pressing research and policy questions. First, by quantifying climate and price variability effects at the farm level, we examine the impacts of climate variability on farm household welfare in Ethiopia. Our study identifies the socio-economic and locational factors responsible for variation across households in their ability to cope with climate and price variability. It captures especially the role of smallholder assets such as livestock and eucalyptus, as well as last-resort emergency measures such as default on credit. Second, we examine the distributional effects of innovation diffusion and productionrelated policy interventions at population level. In particular, we investigate the impacts of new improved maize and wheat varieties in enhancing food security under climate variability. We consider the promotion of mineral fertilizer use, of which current application rates in Ethiopia stand at only 29 kg/ha (Spielman et al., 2011). Using panel data from the central highlands of Ethiopia, Alem et al. (2010) showed that rainfall variability affects fertilizer use decisions negatively, implying that with increasing climate variability, the application of mineral fertilizer and crop yields might further decline.

For computer simulation, we employ a novel stochastic bioeconomic household modeling approach implemented with the agent-based software package MPMAS (Schreinemachers and Berger, 2011). MPMAS is able to simulate agent decision-making while explicitly considering high degrees of heterogeneity, nonlinearity, interaction and feedbacks, and finally emergence (Berger and Troost, 2014). To the authors' knowledge, this study is the first to employ agent-based modeling for quantifying both current climate and price variability effects in Sub-Saharan Africa. With our assessment of potential adaptation options for current agricultural systems under current climate, we contribute to the second core climate impact question raised in the Agricultural Model Intercomparison and Improvement Project (AgMIP, 2015).

Ethiopia is highly exposed to climate variability, as agriculture forms the basis of the economy contributing roughly 43% to GDP, 90% of export earning and 80% of employment (MoFed, 2010). Moreover, agriculture is predominately rain-fed with limited irrigation coverage<sup>22</sup> (Arndt *et al.*, 2011), which means that shift in the timing and amount of rainfall will seriously affect agricultural production and food security (Di Falco and Chavas, 2009). Smallholder farmers cultivating about 95% of the total area under crops and producing more than 90% of Ethiopia's agricultural output are found to be the most affected by current and future climate variability (Milman and Arsano, 2013; Arndt *et al.*, 2011; Deressa, 2009, Di Falco *et al.*, 2011; Block *et al.*, 2008).

Disentangling the effects of climate variability from other determinants of agricultural production and food security is crucial not only to design appropriate climate

<sup>&</sup>lt;sup>22</sup> Currently only about 13% of the potentially irrigable land is irrigated.

mitigation and adaption policies, but also to prioritize interventions. Another determinant of food security that deserves special attention in this context is price variability. The effect of price variability on household food security depends on the rate and speed of productivity-induced changes of market prices, the market position of households (net buyer vs. net seller),the extent of market integration of farm households, as well as changes in wages (Hertel *et al.*, 2010). In line with this, Mideksa (2010), Arndt *et al.* (2011), Robinson *et al.* (2012) and Hertel *et al.* (2010) indicated that analyzing only the production shock effects of climate variability without considering the effects of inherent market forces through price changes would underestimate the effects of climate variability, and hence overestimate the effectiveness of adaptation options.

Against this background, in this paper we make use of numerical simulation to address two highly relevant research and policy questions. First, by quantifying climate and price variability effects at the household level, we examine the impacts of current and future climate variability on farm household welfare in Ethiopia. Our study identifies the socio-economic characteristics responsible for variation across households in their ability to cope with climate and price variability effects. It captures especially the role of smallholder assets such as livestock and eucalyptus, as well as last-resort emergency measures such as default on credit and temporary food shortage.

Second, we examine the distributional effects of production-related policy interventions in agriculture. In particular, we consider the promotion of mineral fertilizer use, of which current application rates in Ethiopia stand at only 29kg/ha (Spielman *et al.* 2011). Using panel data from the central highlands of Ethiopia, Alem *et al.* (2010) showed that rainfall variability affects fertilizer use decisions negatively, implying that with increasing climate variability, the application of mineral fertilizer and crop yields might further decline. In this paper, we seek to examine ways for increasing fertilizer application under climate variability in the form of fertilizer subsidy programs. In addition to fertilizer, we investigate the role of new improved maize and wheat varieties in enhancing food security under increasing climate variability.

For numerical simulation, we employ a novel stochastic bioeconomic household modelling approach implemented with the agent-based modelling software Mathematical Programming-based Multi-Agent Systems ((MPMAS) (Schreinemachers and Berger, 2011)). MPMAS offers the ability to explicitly simulate agent decisionmaking while considering high degrees of heterogeneity, nonlinearity, interaction and feedbacks, and emergence (Berger and Troost, 2014). To the authors' knowledge, this study is the first to employ agent-based modelling for quantifying both climate and price variability effects in the context of Ethiopia. The reminder of the article is organized as follows: section 3.2 briefly introduces the data sources and methods used; section 3.3 presents the results of uncertainty analysis, model validation and scenario design; section 3.4 presents the results of our simulation analysis; section 3.5 discusses our findings and their relevance for climate impact assessments, and section 3.6 concludes with a list of open questions and an outlook on next research steps.

## 3.2 Data Sources and methodology

Climate variability affects farm household income in many ways, notably through changes in crop yields, prices, rural wages and productivity (Hertel et al., 2010). Typically, these effects are household-specific, as households differ in production and consumption decisions as well as in their adaptive capacity (Berger and Troost, 2014). As a consequence, for disentangling the different pathways through which climate variability may affect food security, bioeconomic microsimulation is required. Only then the model can explicitly capture heterogeneity of households in terms of access to resources, poverty levels, and adaptive capacity to climate and price variability. For building our microsimulation model, we applied MPMAS, an agent-based simulation package using whole-farm mathematical programming to simulate farmer decisionmaking in agricultural systems (Schreinemachers and Berger, 2011). MPMAS is available both for Windows and Linux operating systems; under Linux it employs the OpenMPI library for massive parallelization and can optionally be run on highperformance computers. The strength of MPMAS is its ability to capture agent and landscape heterogeneity as well as spatial and social dynamics and interactions (van Wijk et al., 2014). Berger et al. (2006), Berger et al. (2007), Schreinemachers et al. (2007), Schreinemachers et al. (2009), Schreinemachers et al. (2010), Marohn et al. (2013), Quang et al. (2014), Wossen et al. (2014), and Wossen and Berger (2015) demonstrate the empirical use of MPMAS in developing countries. Model equations and software architecture of MPMAS have been described in Schreinemachers and Berger (2011) following the ODD-protocol and are therefore not repeated in this

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article. Here, we give a brief overview of the specific features of this Ethiopian study as compared to other MPMAS applications.

## 3.2.1 Farm household decisions

To represent the heterogeneity of Ethiopian agriculture in our microsimulation model, we parameterized MPMAS for every farm household covered in the Ethiopian Rural Household Survey (ERHS), in total 1,300 households. ERHS, a nation-wide longitudinal data set, is the best available representative household level information, capturing the diversity of agro-ecological conditions across Ethiopia (Dercon and Hoddinott, 2011). According to this survey, the majority of farm households are smallholders operating on 2 ha and less; only few households operate farms with 5 ha and more. The characteristics of each MPMAS model agent, its demographic composition, land rights, ownership of durable assets and geographical location within agro-ecological zones and administrative units directly correspond to a survey household in the ERHS data set.

MPMAS simulates the individual farming decisions of all household agents with Mixed Integer Programming (MIP) to represent the inseparable nature of production and consumption decisions in smallholder subsistence farming<sup>23</sup>. Agents seek to maximize their expected household income by choosing the optimal combination of crop and livestock production and off-farm employment (including seasonal and full-year migration) subject to technological and resource constraints and their consumption preferences. Agent farming decisions, however, are made without perfect foresight about weather and prices in the upcoming cropping season, which may lead to divergence of farm plans and farm outcomes ex-post.

In total, 23 annual crops, 3 livestock types, 7 perennial crops plus eucalyptus were considered as production options in our bottom-up farm-level model. Crop production options available to individual agents as well as crop yields depend on local agroecological conditions at each ERHS site. Crop production functions with respect

<sup>&</sup>lt;sup>23</sup> Ample research on consumption behavior in Ethiopia exists, in particular on the welfare effects of high food prices using utility-based demand models (for example, Tefera et al., 2010; Alem, 2011; Nigussie and Shahidur, 2012). None of these studies, however, captures the non-separability of consumption and production-related decisions of smallholders.

to labor and fertilizer were estimated from IFPRI's Nile Basin survey (Deressa et al., 2009), since production data in ERHS were not sufficiently disaggregated. Crop yields of new maize and wheat varieties were simulated using the Decision Support System for Agrotechnology Transfer (DSSAT version 4.5; Jones et al., 2003; Hoogenboom et al., 2010).

Agent decisions in MPMAS are constrained by available land, household labor and cash reserves, as well as access to technology, off-farm labor markets and different sources of production credit. Land and labor use is disaggregated to monthly balances to capture multiple cropping seasons, peak labor needs and seasonal off-farm employment opportunities. Cash balances distinguish pre- and postharvest cash availability. Further, agent decisions are constrained by the need to cover energy requirements of household members either by producing or buying food. Building on the approach developed by Schreinemachers et al. (2007), consumption decisions of household agents are modeled using a three-stage budgeting procedure with a quadratic specification for the savings function (first stage), a Working-Leser model to determine food expenditure as a share of total expenditure (second stage), and a linear approximation of the Almost Ideal Demand System to allocate the food budget among food categories (third stage). Model parameters were estimated from the expenditure and price information available in the ERHS data. Consumption of self-produced food was valued using local market prices.

Using this MIP formulation with 8,175 columns, 769 rows, and 133 integers, MPMAS simulates three household decisions for each agent within each simulation year: (i) investment decisions and (ii) production decisions at the start of year, (iii) the after-harvest consumption decisions at the end of year.

First, Agents make their individual investment decisions (e.g. planting perennial crops and eucalyptus, keeping livestock, acquire machinery) based on expected long-term resource endowments, yields and prices. Investment options in MPMAS also include the adoption of new improved maize and wheat varieties as promoted by the International Maize and Wheat Improvement Center (CIMMYT). Besides considerations of profitability, adoption of innovations is also subject to individual innovativeness and knowledge constraints. The social diffusion process of innovations is simulated based on the network threshold approach of Valente (1995) as described by Berger (2001). Following Schreinemachers et al. (2009), innovativeness of ERHS survey households was parameterized according to an econometric model estimated from the recent Sustainable Intensification of Maize and Legume Systems for Food Security in Eastern and Southern Africa (SIMLESA) survey (Teklewold et al. 2013).

Second, agent production decisions (e.g. land and input use for crops and livestock) are based on resource availability and food consumption needs for the imminent season. Note that in MPMAS (as in real-world farming), these agent production decisions are made without perfect foresight using expected short-term yields and prices. Climate and price variability can thus lead to reduced household income expost, because agent might have planted the "wrong" crops and their fertilizer management was not optimal.

Third, after harvest, actual crop yields and prices are known by agents, but production can evidently not be changed anymore. In case of unforeseen favourable climate and price shocks, agents forgo the income earning opportunities they could have exploited with perfect foresight. In case of adverse shocks, agents have to adopt ex-post coping measures to mitigate the negative impacts on livelihood and especially food security. The coping measures at agent level include purchase of additional food, consuming different, less expensive or inferior food, or distress sales of livestock or eucalyptus. If coping measures are insufficient to satisfy the individual food energy needs in MPMAS, agents default on credit (if taken) and/or run into food energy deficits. Table 3.1 shows the agent coping measures and frequencies of adoption as simulated in MPMAS.

Ex-post coping measure	Indicator used	Frequency of
		adoption
Migrate temporarily to earn more	Off-farm employment	15%
cash		
Buy more food	Savings used for food purchase	13%
Consume less preferred food	Reduction in most preferred food	97%
	items (teff, wheat, barley, maize)	
Reduce non-food expenditure	Reallocation from non-food to food	51%
	expenditure	
Sell eucalyptus trees	Revenues from distress sales	6%
Sell livestock	Revenues from distress sales	24%
Default on credit	Loans and interests not repaid	2%

Table 3.1: Agent coping measures simulated in MPMAS

Note: Column 3 reports the frequencies of coping measures adopted by agents who run into food energy deficits in the baseline scenario, albeit their ex-post coping attempts

## 3.2.2 Climate and price variability

Climate-related events such as drought, excessive rainfall, high temperature, frost etc. affect specific crop yields negatively and to different degrees. Crop data from the Ethiopian Central Statistical Agency (CSA), including yield damage assessments, were used to compute crop yields for very dry, dry, normal, wet and very wet years at each site of the ERHS. Corresponding crop damage factors for new maize and wheat varieties were derived from DSSAT simulations. The frequency distribution of very dry, dry, normal, wet and very wet years were varieties were derived from DSSAT simulations. The frequency distribution of very dry, dry, normal, wet and very wet years—whereby *wetness* of years was classified using the standardized annual rainfall anomaly index—was calculated using a 30-year time-series of historical rainfall records (1980-2009) obtained from the National Meteorology Agency (NMA) of Ethiopia.

According to ERHS, also prices on agricultural markets vary considerably between years and surveyed sites, and this local price variation was considered accordingly in our microsimulation model. For the analysis of inter-temporal price variability, we made use of local output prices covered in the various rounds of ERHS and imputed missing values for the years in between from EGTE (Ethiopian Grain Trade Enterprise), CSA and FAOSTAT. To obtain time series of 16 years (1994-2009) with local prices corrected for inflation and market trends, we employed the following

procedure: First, we transformed nominal prices to 2009 real terms and used the transformed data for estimation of mid-term linear trends for each farm output at each ERHS site (35 output prices at 15 sites over 16 years). Second, we computed residuals for each local farm output as the difference between real prices and the predicted trend line. Finally, we generated 16 years of local de-trended real prices as the sum of yearly residuals and the 2009 real price.

When correlating local crop prices with local rainfall, we found negative linear association with Pearson's r ranging from -0.860 to -0.541 at the various ERHS sites. Only in 3 instances, where farmers did not produce all crops traded on the local market, correlation took on positive values of up to 0.600. For all sites of the EHRS taken together, Pearson's r reached a value of -0.194 (significant at the 1% level). We then assigned the 16 years in our price time series to the wetness class that each year belonged to. Since our 16-year dataset did not contain prices under very dry conditions, local prices for one additional very dry year were extrapolated.

## 3.2 Simulation

#### 3.2.1 Scenario and experimental design

To simulate the impacts of climate and price variability on household poverty and food security, we ran the MPMAS model over a simulation horizon of 15 years. For each of these 15 simulation years, a specific wetness value was sampled from the probability distribution of wetness classes. The CSA crop damage factors associated to the determined wetness class were then applied to determine local crop yields obtained by model agents in this model year. Likewise, a vector of local market prices was drawn randomly from the price observations associated to this wetness class. In this way, the observed correlation of local rainfall, yields and prices was preserved in the sampling procedure.

For policy impact analysis, we simulated innovation diffusion (new maize and wheat varieties) and two policy interventions that could help farmers cope with climate and price variability. As the adoption of new crop varieties implies additional cash requirements for buying seeds, the first policy intervention considered in MPMAS was improving access to short-term credit for productive purposes. In the baseline MPMAS parameterization, agent access to credit followed the ERHS (2009) information

according to which only 12% of the households received credit from microfinance organizations (interest rate of 18% p.a.) and 22% received credit from the government (interest rate of 9% p.a.). With the first policy intervention, all agents were given the opportunity to take short-term credit at the onset of the cropping season for all production-related cash outlays using interest rates of current microfinance programs in Ethiopia. As new crop varieties also have higher fertilizer demands, we considered fertilizer subsidies as another potential policy intervention. Currently, Ethiopia has no formal fertilizer subsidy, lack of which can aggravate cash constraints of smallholder farmers. Our second policy intervention introduced fertilizer subsidies of 25% following expert suggestions. We tested both the isolated and combined effect of each policy intervention compared to no intervention.

To be able to quantify the income effect of climate and price variability, we also ran one counterfactual scenario without any variability (average yields and prices, no policy interventions). Further, we ran two scenarios where we assumed ideal technical change (i.e. full access for all agents to innovation immediately), one without policy interventions and one with both credit and fertilizer subsidies.

As argued by Berger and Troost (2014), bottom-up farm level models are inevitably subject to considerable model parameter uncertainty, which should be clearly communicated to the reader by reporting model results of the full range of potential parameter settings. We identified 23 major uncertain parameters in our microsimulation model. The first parameter constituted the actual 15-year-weather/price sequence drawn from the frequency distribution and thus accounts for the *aleatory* uncertainty in simulated variability. The other 22 parameters represented *epistemic* uncertainty in the model implementation.

An efficient sampling scheme was therefore paramount to represent the uncertain parameter space in as few model runs (and as little model run time) as possible. We achieved this by using a Sobol' sequence, a quasi-random sampling approach that tends to converge considerably faster than standard Monte-Carlo methods (Tarantola et al. 2012). When testing all 7 scenario settings to be analyzed in this study, we found that convergence of differences in agent incomes was reached within 100 repetitions. Since each scenario was simulated using the same Sobol' sequence of parameter vectors, each point of the sequence provides a fully controlled experiment that isolates the scenario effect on each individual agent from any variation in other parameters. Mean effects and confidence intervals can therefore be calculated directly from the simulated distribution of the scenario effect over all points of the sequence.

#### 3.2.2 Model validation

Before running the policy scenarios, we assessed the reliability of our model simulations by running validation experiments comparing simulated food expenditures and land uses to the survey observations of ERHS (2009). To avoid over-fitting the model and deteriorating its out-of-sample properties, we evaluated the full space spanned by the uncertain model parameters as suggested by Troost and Berger (2015) and did not calibrate the model for perfect fit to one single point observation.

For these validation experiments, we ran the model for one simulation year using pre-2009 long-term price and yield damage averages to initialize agent expectations and the actual 2009 price/ yield damage vectors to simulate agent land use and food consumption. The validation experiments were run for 100 points of the Sobol' sequence described above. Figure 3.1 shows the simulated and observed distributions of per-adult equivalent food expenditure over all households of the agent population. On average over the 100 points of the sequence, MPMAS achieved a Nash-Sutcliffe model efficiency of 0.54 (minimum 0.44, maximum 0.59) in simulating the observed distribution of per-adult food expenditure. As the graph illustrates, deviations from the observed distribution mainly result because MPMAS partly overestimates the share of low-income households with per-adult food expenditures around 1500 Birr. This also results in a slight overestimation of the incidence of food poverty (39% on average over 100 repetitions compared to 35% in the ERHS)<sup>24</sup>. Since we had to complement the ERHS survey with crop yields and production functions from other data sources, we accepted the model efficiency achieved as sufficiently high for this explorative study.

<sup>24</sup> Calculated using the official Ethiopian food poverty line of 1665 Birr (in 2009 prices).



Figure 3.1: Validating the distribution of per-adult food expenditure

As the second indicator for model validation, we compared the area a surveyed household cultivated with its most important crop to the area the corresponding model agent allocated to that crop. The model efficiency for this indicator reaches 0.69 with very little variation over the 100 repetitions. Figure 3.2 presents the simulated and observed area distributions for the households' main crop. The simulated distribution fits the observed one pretty well, but is a bit shifted to the left, because of rounding errors when representing small plot sizes in MPMAS<sup>25</sup>.

<sup>25</sup> In this study, we set cell size to 0.125 ha. As agent land endowments can only be represented in MPMAS as multiples of this value, very small land holdings are more affected by rounding up or rounding down.



Figure 3.2: Validating the distribution of household's most important crop

## 3.3 Results

This section presents our simulation results divided into two parts: (1) effects of current climate and price variability, (2) impacts of technical change and policy interventions. The outcome indicators used are per-adult equivalent household income (to measure the impacts of policy intervention and technology diffusion) and per-adult equivalent food expenditures (to measure changes in food security).

## 3.3.1 Current climate and price variability

In order to assess the effects of climate and price variability, we ran 100 repetitions of a baseline scenario with current climate and price variability and 100 repetitions of a counterfactual scenario without any climate and price variability. As expected, we found mostly adverse effects of climate and price variability on agent incomes: on average, agent incomes were about 5% higher in the counterfactual scenario without any variability. A closer investigation at the household level – Figure 3.3 ranks the individual agents by their average per-adult baseline income over all repetitions and years–, reveals considerable variation across agents when coping with climate and price variability.



Figure 3.3: Income change in counterfactual without any variability compared to baseline

Co		e with climate	h climate and price variability			
unterfac	All values in percent	Always poor	More often poor	Less often	Never poor	Row sums
tual v	Agents always poor in all repetitions and years	9 <sup>1</sup>	5 <sup>11</sup>	poor		14
vithout	Agents more often poor than non-poor (>50%) in all repetitions and years		21	0		22
any var	Agents less often poor than non-poor (<50%) in all repetitions and years		1	22		23
iabili	Agents never poor in any			$17^{iv}$	$24^{iii}$	41
ty	Column sums	9	28	40	24	100

Table 3.2: Food poverty position of agents with and without climate and price variability

Note: Table is based on simulated per-adult food expenditures, compared pairwise for each agent in all 100 repetitions and 15 years, using identical Sobol' sequences in both scenarios. An agent household is counted as 'poor' when its per-adult food expenditure is below the offical food poverty line of 1,665 Birr per adult equivalent. Cells are indexed as follows: (i) Agents that are always poor in all 100 repetitions and 15 years, both with and without climate and price variability, (ii) Agents that are always poor without variability, but more often poor than non-poor with variability, (iii) Agents that are never poor with and without climate and price variability, (iv) Agents that are never poor without variability, but more often poor with variability, (iv) Agents that are never poor without variability, but more often poor with variability.

Table 3.2 disentangles the variation of food security across agents, considering all 100 repetitions and all 15 years that were simulated in both scenarios (i.e., pair-wise comparisons of 1,500 data points per agent). The table matches the food poverty

position of agents in terms of per-adult food expenditures in the baseline scenario and the counterfactual scenario. The column sum in the first column, for example, indicates the share of agents that were always poor in all repetitions and years in the baseline with climate and prices variability. Likewise, the row sum in the first row indicates the share of agents that were always poor in all repetitions and all years in the counterfactual scenario without variability. On the diagonal, we find the agents whose food poverty position did not change across these two scenarios. Accordingly, 9% of all agents remained always poor both under variable and constant conditions (cell in table indexed as i). Interestingly, 5% of the agents achieved a higher level of food security with climate and price variability.

They were always poor without climate and price variability but gained more in above-average years than they lost in below-average years. As a consequence, they appear in the off-diagonal cell (indexed as ii) of agents that were more often poor than non-poor in the baseline (i.e., below the food poverty line in more than 50% of the 1,500 repetitions and years). Table 3.3 shows that these agents who improved their food poverty position with climate and price variability (column indexed as ii) had, on average, larger initial land sizes, more frequent access to improved seed and applied more mineral fertilizer than agents whose food poverty position remained unchanged (column indexed as i).

Moreover, Table 3.2 shows that 24% of all agents were never poor in both scenarios, i.e. their food security was unaffected by climate and price variability (cell in table indexed as iii). For 17% of all agents, however, the food poverty position deteriorated under climate and price variability. These agents were never poor without climate and price variability but were driven at least sometimes into food poverty under variability conditions and appear in the off-diagonal cell (iv) of agents that were less often poor than non-poor in the baseline (i.e., below the food poverty line in less than 50% of the 1,500 repetitions and years). As shown in Table 3.3, these agents with deteriorating food poverty position (column iv) had, on average, less usable land, they initially owned less perennials and less eucalyptus but more livestock than agents that remained unaffected by climate and price variability (column iii). They also applied less improved seeds and less fertilizer.

Table 3.3: Comparison of agents whose food poverty position changes with climate and price

#### variability

	(i) 'Alwa	iys poor'	(ii) 'Mor	e often	(iii) 'Nev	er poor' in	(iv) 'Less of	ten poor'
	scen:	arios	yarib	ility	boin		under variability	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD
variable	Median	50	Median	50	Median	50	Median	50
Household size	7.33	(6.68)	6.68	(2.45)	3.27	(1.69)	5.65	(2.15)
(members)	7.00	(0.00)	7.00	()	3.00	()	5.00	()
Innovativeness	2.95	(0.96)	2.80	(0.96)	2.12	(1.00)	2.22	(1.04)
(0 = innovator, 4 =	3.00		3.00		2.00		2.00	
laggard)								
Usable land area per	0.09	(0.41)	$0.11^{***}$	(0.08)	1.28	(2.24)	$0.58^{***}$	(0.48)
adult equivalent (ha)	0.05	. ,	0.11	· /	0.87	. ,	0.49	. ,
Livestock herd size	0.10	(0.18)	0.17	(0.33)	3.37	(18.90)	$4.12^{***}$	(41.70)
(tropical livestock	0.00		0.00		1.73		0.78	
units)								
Perennial area per	156.4	(234.8)	324.9	(483.4)	443.2	(1907.3)	$200.3^*$	(423.2)
adult equivalent (m <sup>2</sup> )	39.4		105.2		0.0		0.0	
Eucalyptus area per	19.2	(41.0)	35.4	(69.5)	267.4	(794.6)	$92.3^{*}$	(288.0)
adult equivalent (m <sup>2</sup> )	0.00		0.00		0.0		0.0	
Credit	0.14	(0.35)	0.12	(0.32)	0.37	(0.48)	0.34	(0.47)
(1 = has access)	0.00		0.00		0.00		0.00	
Improved seed	0.44	(0.50)	$0.58^{***}$	(0.49)	0.81	(0.39)	$0.87^{***}$	(0.34)
(1 = has access)	0.00		1.00		1.00		1.00	
Off-farm employment	0.11	(0.32)	0.15	(0.35)	0.06	(0.24)	0.04	(0.20)
(1 = has access)	0.00		0.00		0.00		0.00	
Variability of local	0.32	(0.15)	0.35	(0.16)	0.35	(0.11)	0.35	(0.10)
production value	0.22		0.23		0.34		0.34	
Fertilizer used (kg)	4.8	(7.6)	12.6***	(19.2)	129.7	(374.7)	128.5***	(126.5)
	0.00		6.2		47.8		94.0	
Number of agents	115		69		307		226	

Note: Columns refer to the indexed cells in Table 2. Results of Mann-Whitney tests are reported as follows: \* Significance at 10% level. \*\* Significance at 5% level. \*\*\* Significance at 1% level. We used non-parametric testing instead of parametric testing as variable means do not represent well the centers of distribution.

Apparently, not only initial asset endowments determined the adaptive capacity of agents and especially their successful coping with unforeseen climate and price shocks. Eventually, their food poverty position might also have been affected by access to financial markets (credit) and labor markets (off-farm employment), as well as farm location (agro-ecological zone) plus climatic conditions and correlated output prices (production value). As agents have to deal with the consequences of imperfect foresight, increasing agricultural intensity (fertilizer, improved seed) can lead to a leverage effect, when financed with credit.

	'Always poor' (i) vs.		'Never poor' (iii) vs.	
	'More often poor' (ii)		'Less often poor' (iv)	
Variables	Marginal effects	(model 1)	Marginal effects (model 2)	
Household size	- 0.041***	(0.0120)	0.116***	(0.0090)
Innovativeness	- 0.024	(0.0320)	0.072***	(0.0180)
Perennial area	0.001***	(0.0001)	- 0.000**	(0.0000)
Eucalyptus area	0.001***	(0.0006)	- 0.000	(0.0000)
Credit	0.028	(0.1250)	- 0.080	(0.0870)
Improved seed	0.016	(0.0930)	0.074	(0.0580)
Variability of production value	0.605**	(0.2570)	0.415**	(0.1840)
Fertilizer	0.020***	(0.0067)	- 0.001	(0.0006)
Credit * fertilizer	- 0.025***	(0.0094)	- 0.000	(0.0003)
Credit * improved seed	0.375**	(0.1760)	- 0.049	(0.0670)
Cool sub-moist mid highlands	0.484***	(0.1440)	- 0.263***	(0.0960)
Tepid sub-moist mid highlands	0.430***	(0.1400)	- 0.187**	(0.0940)
Tepid moist mid highlands	0.490***	(0.1600)	- 0.182*	(0.0970)
Tepid sub-humid mid highlands	0.068	(0.1190)	- 0.099	(0.0900)
Other controls	Yes		Yes	
Pseudo R <sup>2</sup>	0.35		0.33	
Ν	184		533	

Table 3.4: Factors influencing the simulated change of food poverty (Probit regressions)

Table 3.4 reports the results from Probit regressions to test the influence of these factors on the probability of changing the agent food poverty position under climate and price variability. Agents with initially smaller household sizes and larger endowments of perennial crops and eucalyptus were less likely in the 'always poor' position (cell i) and more likely in the 'more often poor than non-poor' position (cell ii). In addition, agents with higher application of mineral fertilizer were more likely to have higher food security under climate and price variability. Interestingly, while the marginal effect of fertilizer alone was positive and significant, the interaction term between credit and fertilizer turned out to be negative and significant, indicating that agents who bought fertilizer through credit were less likely to have higher food security under climate and price variability.

As explained above, MPMAS implements rather strict repayment of credit that works as leverage in case of below-average years. Still, the interaction term between credit and improved seed was positive and significant, implying that agents who had access to improved seed and took credit were more likely to achieve higher food security. Moreover, we found that the extent of local climate and price variability has a positive and significant effect on the food poverty position of agents in cell ii. (As a measure for climate and price variability at each ERHS site, we used the coefficient of variation of production value calculated by dividing the standard deviation of total production value at one site by its mean.) In addition, we found location-specific effects of the various agro-ecological zones.

Table 3.4 also reports Probit results for the agents that were 'never poor' in both scenarios (cell iii) and for the agents who were 'never poor' without climate and price variability but 'less often poor' than non-poor under variability (cell iv). We found that initial household size and endowment with perennials were important factors associated with a deteriorated food poverty position due to climate and price variability. Furthermore, agents who were less innovative were less likely found in the 'never poor' position than in the 'less often poor' position. The same applied to agents at ERHS sites with higher variability of production value: their food security was more likely to be lower with climate and price variability. The effects of agricultural intensification and credit leverage were not found to be significant for agents in cells iii and iv.

This set of baseline scenarios corresponds to the standard simulation analysis applied in agent-based bioeconomic modelling (e.g., Schreinemachers *et al.* (2010)), where each individual agent is modelled recursively over a period of 15 years and some form of agent interaction is incorporated. Figure 3.5 shows the distribution of agent percapita income under baseline conditions (i.e. under current credit availability and levels of technology diffusion) averaged for each agent over 15 years. This figure also includes a vertical line at the income of 1.25 US\$ per person, showing that about 40% of the agent population lies below this poverty line in the hypothetical scenario without climate and price variability<sup>26</sup>.

<sup>&</sup>lt;sup>26</sup> The baseline is not a forecast, but instead provides a counter-factual—a reasonable trajectory of poverty in the absence of climate change that is used as a basis for comparison with the various climate change scenarios. We choose the baseline as a situation without any climate and price variability since a lack of an appropriate comparison unit may pose challenges for impact estimation. As a baseline, one can for example use the current levels of variability as a benchmark. However, without establishing how household income would have evolved without any climate variability, it is almost impossible to estimate the impact of climate variability on household income. Accordingly, this baseline is used to show the impacts of variability but not the effectiveness of policy interventions.

## **3.4** Technical change and policy interventions

Since we simulated agent decisions recursively over a 15-year horizon, we could observe trajectories of individual agents under climate and price variability. Over the years, agents accumulated assets and adopted new maize and wheat varieties according to their innovativeness. Figure 3.4 shows the evolution of agent incomes in the baseline averaged over the 100 repetitions. Although agent incomes were growing with increasing variation, the growth in agent income was quite modest for the lower income quartiles.<sup>27</sup>



Figure 3.4: Trajectories of baseline agent incomes

In addition, our simulations allow us to analyze the impacts of the five policy scenarios we implemented: (i) perfect information communication through agricultural extension to speed up technology diffusion ("ideal technical change"); (ii) expansion of credit availability; (iii) fertilizer subsidy; (iv) expansion of credit availability together with fertilizer subsidies; (v) perfect information communication together with expansion of credit availability and fertilizer subsidies. Note that the scenarios (i) and (v) with ideal technical change reveal the maximum possible effect of information

<sup>27</sup> We switched off population growth in our simulation experiments presented here to facilitate intertemporal comparisons in a straightforward manner. With population growth, agent incomes grew slower in the upper quartiles and stagnated/declined in the lower quartiles.
communication at the individual agent level. Both scenarios assume a perfectly working agricultural extension service, so that all agents receive immediate access to novel maize and wheat varieties.

Figure 3.5 compares the impacts of the policy interventions, considering all 100 repetitions and 15 years for each individual agent. On average, all interventions were effective in improving agent incomes under climate and price variability, although policy impacts on agent incomes differed in mean and ranges. Policy intervention (ii) "credit" showed the smallest positive shift of income (1% on average), intervention (i) "ideal technical change" and intervention (iii) "fertilizer subsidy" showed minor shifts (2%), while intervention (iv) "credit plus fertilizer" had a medium shift (3% on average), and intervention (v) "Ideal technical change plus credit and fertilizer" the largest shift of income (4% on average). As can be seen, however, policy impacts showed large variation and were not evenly distributed. Median values were much lower than mean values and everywhere negative.



Figure 3.5: Income change under various policy interventions compared to baseline

Table 3.5 unravels the policy impacts under climate and price variability in a few more dimensions. In terms of winning and losing income, all policy interventions enabled agents at least in 44% of the repetitions and years to maintain or increase their income as compared to the baseline. In 56% of the cases, agents lost income as compared to

the baseline. "Ideal technical change plus credit and fertilizer" produced most incidences of identical or higher agent income (49%) and "credit" fewest (44%).

Indicator	Scenario					
	Baseline	Ideal technical change <sup>(i)</sup>	Credit <sup>(ii)</sup>	Fertilizer subsidy <sup>(iii)</sup>	Credit + fertilizer subsidy <sup>(iv)</sup>	Ideal technical change + credit + fertilizer <sup>(v)</sup>
Incidence of successful adaptation (%)	-	45	44	46	47	49
Incidence of food poverty (%)	37	36	36	36	36	35
Agents always above poverty line (%)	24	28	28	27	28	28
Agents always below poverty line (%)	9	8	8	8	8	7
Break-even policy costs, mean and standard deviation (Birr/HH/year)	-	256 (98)	134 (95)	167 (87)	236 (112)	484 (142)

Table 3.5: Policy impacts and break-even points

Note: Indices (i) to (v) refer to the various policy scenarios. 'Incidence of successful adaptation' is computed as follows: for all agents in all repetitions and years, we counted the number of cases in which an individual agent maintained or increased its baseline income and related the total number of these cases to the number all simulated agent incomes. Likewise, 'Incidence of food poverty' refers to the percentage of cases in which an individual agent was below the offical poverty line measured in terms of per adult food expenditures. 'Breakeven policy costs' considers the discounted stream of agent income increase through policy intervention and subtracts the discounted stream of costs for subsidizing credit and fertilizer plus losses due to credit default (based on market prices, discount rate 6% p.a.).

In terms of food security measured by food expenditures, all policy interventions reduced the incidence of food poverty by 1% and "Ideal technical change plus credit and fertilizer" by 2%. The policy impacts on the 'never poor' and 'always poor' agents, however, differed. In the 100 repetitions and 15 years of the baseline scenario, 24% of the agents were always above the official poverty line of 1,665 Birr per-adult food expenditures (cell iii in Table 3.2). With policy intervention, this share of non-poor agents increased to 27% ("fertilizer subsidy") and 28% (all other interventions). Alternatively, 9% of the agents (see Table 3.2) were always below the official poverty line in the baseline; with policy intervention this share of agents decreased slightly to 8% and 7%. The policy interventions were thus more effective on the 'never poor' than on the 'always poor' side of the farm household population.

In addition, Table 3.5 provides estimates for break-even points of policy implementation, valued at market prices and without considering possible spillover effects to the non-farm rural sector. We derived these break-even points from the stream of discounted increase in agent incomes, subtracting the stream of discounted policy costs related to credit/fertilizer subsidies and credit default. The break-even points hence indicate an upper level for policy implementation: as long as policy administration costs do not exceed the break-even point, direct policy benefits will be higher than the respective policy costs. According to our simulations, the break-even point of implementing additional credit programs is, on average, 134 Birr per household and year with a standard deviation of 95 Birr in all repetitions and years. Compared to credit, the break-even point for fertilizer subsidy is a bit higher in terms of mean and a bit lower in terms of standard deviation. Implementing combined programs for credit plus fertilizer subsidy leads to an almost twice as high break-even point, without much increase standard deviation. The break-even point for implementing perfectly working agricultural extension is 256 Birr per household and year, and when combined with credit and fertilizer subsidies 484 Birr. In the latter case, standard deviation increased to 142 Birr per household and year.



Figure 3.6: Income change under policy intervention (v) compared to baseline

Figure 3.6 shows the distribution of policy benefits for the scenario "Ideal technical change plus credit and fertilizer" across the agent population (distributions for all

other interventions are not reported here as they look similar). Despite much variation in relative income changes, the policy interventions tested in our study generally benefit households with higher baseline incomes more than households with lower baseline incomes.

# 3.5 Discussion

In this section, we interpret the results of our simulation experiments, addressing the two main research questions posed in the introduction: (i) what are the likely impacts of climate and price variability on farm households in Ethiopia, and considering this variability (ii) how could policy interventions in response to current climate and price variability affect food security outcomes? We also ran test simulations of smallholder adaptation to climate change but do not report results here, due to the large model uncertainties of available predictions for future rainfall patterns (Ehret et al., 2012). Fortunately, there is potential to improve regional climate simulations in the next years by operating the models on convection permitting scale (Warrach-Sagi et al. 2013). Still, we believe that our present results contain useful policy insights also for future conditions in agreement with the statement of Arribas et al. (2011): *"There is no better way of adapting to climate change tomorrow than adapting to climate variability today"*.

#### 3.5.1 Impacts under climate variability

Climate and price variability offer opportunities and threats to agriculture that could if smallholders had perfect foresight at the onset of the cropping season—be exploited or mitigated by anticipating the optimal crop choice and crop management accordingly. In reality, however, smallholder farmers usually make land-use decisions that are optimized for "normal" average years, including some margin of flexibility and risk aversion. As a consequence, benefits in years more favorable than expected cannot be fully exploited, and losses in years more adverse than expected cannot be fully avoided. This implication of imperfect foresight has been quantified in MPMAS by running simulation experiments with and without climate and price variability. According to our stochastic simulations, the effects of variability lead to a 5% reduction of agent income, on average, but with considerable variation. Variability generally aggravates food security, but simultaneously in 4 of 10 cases agent incomes were equal or even higher than in the counterfactual scenario without any variability. Our simulation results thereby underline the importance of considering agent heterogeneity in integrated assessment studies of climate-adaptation policies.

#### 3.5.2 Failure of agent coping measures

According to Cooper et al. (2008), farm households in developing countries use both ex-ante and ex-post coping measures in response to climate and price variability. In our simulation experiments, we implemented various coping options such as planting new crop varieties (ex ante measure) and purchasing additional food, consuming less expensive and inferior food as well as ensuring additional cash inflows through temporary migration (all ex post measures). Some of the coping measures implemented here, however, are last-resort decisions that households are only willing to make under extreme hardship. These involve for example distress sales of assets, defaulting on credit and – in case that all these measures fail – severe food shortages. The above mentioned coping measures are crucial for smallholders in rural Ethiopia since many of them are poor and vulnerable to deviations in production value due to climate and price variability. Our simulations show that the effects of climate and price variability on household food security are considerable: 14% of the agents are always below the food poverty line; only 41% are never poor in any of the 100 repetitions and 15 years. Therefore, our simulation results suggest that 'self'-coping options are important but not sufficient and should be complemented with appropriate policy interventions.

#### 3.5.3 Effectiveness of policy interventions under current climate variability

Policy interventions aimed at promoting new crop varieties appear to be effective in our simulations if implemented under optimal conditions (that is, if innovation diffusion could be sped up to the maximum through farm extension, and credit and fertilizer subsidies were used on-farm for productive purposes only). Under these optimal conditions (and additional costs of policy administration below certain limits), the three types of policy intervention benefit especially the agents with higher baseline incomes. The reversal conclusion is, therefore, that more targeted policy interventions are needed in Ethiopia to address the very poor, for example, interventions to strengthen their safety nets (Wossen et al., 2015).

#### 3.5.4 Model limitations

Finally, we would like to discuss the model limitations and comment on the credibility of our simulation results. As mentioned above, this study uses the sampling frame and data from ERHS; where data gaps needed to be filled, we complemented ERHS with other datasets such as IFPRI's Nile Basin survey and CIMMYT's SIMLESA technology adoption survey. For the lack of detailed crop yield data, we had to rely on national average damage assessments of CSA for calibrating crop yield responses. Considering these data limitations, we achieved a surprisingly high level of model efficiency, especially for bottom-up farm-level models. We expect to improve model efficiency further, once results from crop-growth simulations become available for all important crops and locations and consistent crop production functions can be included in MPMAS.

Cross-checking with local experts confirmed large resemblance with actual adaptation behavior of smallholder farmers in Ethiopia, although certain decision rules in case of severe food shortages (whether to default on credit or not) require more empirical investigation. In our agent model, we could not yet implement local safety nets and kinship ties (Wossen et al., 2013). Implicitly, we assumed that these smallholder support networks could help to recover agent livelihoods to the extent that agents would again receive credit after credit default and survive even in case of severe food shortages.

# 3.6 Conclusions

This study applied stochastic bioeconomic household modeling to analyze smallholder adaptation to climate variability in Ethiopia. It used the agent-based simulation package MPMAS, which allowed capturing non-separable production and consumption decisions under price volatility, the role of livestock and eucalyptus as means of consumption smoothing, default on credit and temporary food shortages, as well as policy options related to the promotion of new crop varieties such as innovation diffusion, credit and fertilizer subsidies.

Our simulation results point to several important findings. First, the study underscores that climate and price variability indeed matters for smallholder agriculture in Ethiopia, and both autonomous and planned adaptation options are urgently needed.

We found that the promotion of new crop varieties through improved information communication was an effective adaptation option on average. In addition, adaptation strategies composed by a portfolio of interventions (new crops accompanied by credit and fertilizer subsidies) were more effective compared to single-measure interventions.

Second, our simulations suggest that the effectiveness of specific adaptation options is quite different across the agent population. In particular, while households with more abundant asset endowments and higher farm incomes were largely able to cope with variability especially through the promotion of new crop varieties, most households with a limited asset base were found to be vulnerable. Moreover, while policy impacts on agent incomes were positive on average, median impacts were in all cases negative. This implies that policy recommendations based on average impacts may mislead policy makers to adhere to interventions which are beneficial for average farm households, albeit ineffective in addressing the needs of the poor and food insecure farmers. As a consequence, new planned adaptation options for the very poor might get less support in favor of options which are rather effective for households who could have coped relatively well with the effects of climate variability through autonomous adaptation options.

Third, the simulation experiments suggest that more innovation is definitely needed to alleviate poverty and improve food security among smallholder farmers in Ethiopia. It would, therefore, be highly interesting to include in our simulation analysis new stress-tolerant crop varieties developed in current plant breeding programs as additional technology options in MPMAS. The simulation-based assessments could then be repeated in MPMAS, yielding possible new insights for research prioritization and policy development. In addition, it might also be worth to integrate MPMAS with economy-wide CGE and/or global trade models so that improved price variability scenarios can be run as suggested by Berger and Troost (2014).

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# **Chapter Four**

# 4 Social capital, risk preference and adoption of improved farm land management practices in Ethiopia

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#### Abstract

Many developing countries grapple with high rates of farmland degradation and low agricultural productivity amidst increasing climate variability. Considerable efforts have been exerted to promote the diffusion of improved farmland management to address these challenges. Despite these efforts, adoption rates, especially of soil conservation and water harvesting technologies, are still low, which has been the subject of investigation in several studies in Ethiopia and elsewhere. Most studies on the adoption of these technologies, however, tend to focus on economic incentives only, paying little attention to the role of social capital. This paper provides evidence of the effects of different dimensions of social capital on innovation adoption across households holding different levels of risk-aversion. We address this issue by using cross section and panel data from Ethiopia. Results show that social capital plays a significant role in enhancing the adoption of improved farmland management. We also find evidence that the effect of social capital across households with heterogeneous risk taking behaviour is different.

### JEL classification: C36, C93, D71, D81

*Keywords*: Innovation adoption, Soil conservation and water harvesting, Smallholder agriculture, Ethiopia

#### 4.1 Introduction

In many developing countries, resource depletion and land mismanagement associated with limited or lacking soil and water conservation are the main drivers of land degradation. According to Teklewold and Kohlin (2011), Ethiopia, for example, loses 4.2 tonnes of fertile soil per hectare per year. This may aggravate the food insecurity and poverty levels of the country, worsening the already staggering economy characterized by skimpy agricultural productivity with little investment and limited ability to cope with shocks. Studies such as Kassie *et al.* (2012) clearly show that soil conservation and water harvesting play a crucial role in sustaining crop yields by increasing soil moisture. In the current Growth and Transformation Plan (GTP) of the country, the notion of resource management-based agricultural systems has therefore been given emphasis at the policy level. In line with this strategy, different forms of interventions ranging from economic incentives to coercive measures have been implemented to encourage the adoption of improved land management practices such as soil conservation and water harvesting technologies. Despite these efforts, adoption has been limited<sup>28</sup> and the problem of land degradation, especially through soil erosion, persists in the cereal-growing areas of the northern and central highlands of the country.

One factor that deserves more attention in this context is the social capital aspect related to improved farmland management (Isham, 2002). For the case of Ethiopia, previous empirical studies on agricultural technology adoption have largely focused on economic incentives (Gebremedhin and Scott, 2003; Bewket, 2007; Kassie *et al.*, 2012; Pender and Gebremedhin, 2006), giving little attention to the role of social capital. One notable exception is the study of Di Falco and Bulte (2013) who used cross-sectional data from the Nile basin of Ethiopia and found that the size of kinship (as measured by the number of relatives living in the same village) has a negative and significant effect on the adoption of soil and water conservation technologies. While this seems to be a plausible result, it does not provide a comprehensive causal

<sup>&</sup>lt;sup>28</sup> A plethora of possible explanations have been provided in the literature. These include household endowments of physical and human capital (Asfaw and Admassie, 2004; Pender and Fafchamps, 2006), exposure to agricultural extension (Abrar *et al.*, 2004), limited off-farm opportunities (Pender and Gebremedhin, 2006), limited profitability (Croppenstedt et al., 2003; Dadi *et al.*, 2004, Consumption risk (Grepperud, 1997), poverty (Shively, 2001), population pressure (Grepperud, 1996) and tenure insecurity (Holden and Yohannes, 2002).

relationship between adoption of land management practices and the different forms of social capital as the approach was limited in scope, focusing mainly on a single social capital indicator. The focus of this article is therefore to examine how an individual's access to social capital may impact adoption of profitable land management practices by reducing some of the prevailing market inefficiencies and supply side constraints of adoption. Examples of market imperfections that impede adoption that may be reduced through social capital include missing markets for risk, credit, labour and information (Jack, 2011; Shiferaw *et al.*, 2009). In particular, we included several dimensions of social capital in order to shed more light on the differential effects of the type and size of social capital on the adoption of improved farmland management practice in Ethiopia.

We further seek to contribute to the technology adoption literature by focusing on one important behavioural parameter: attitude towards risk. The effect of risk-aversion on the adoption of land management strategies is well documented (Teklewold and Kohlin, 2012; Kassie *et al.*, 2010). However, there appears to be a scarcity of empirical studies that address the effects of social capital across households holding different levels of risk attitudes. This is particularly important since heterogeneity of risk attitudes might affect the formation of social capital and groups. Attanasio *et al.* (2012) pointed out that among close family and friends, individuals with similar risk attitudes are more likely to group together. In the same line, Nielsen *et al.* (2013) indicated that network reliance with first-degree relatives has a positive impact on risk-aversion. If risk-aversion affects the formation of links and networks, then the effect of social capital across households holding heterogeneous risk attitude levels could be very different.

Capturing the effects of social capital across households holding different levels of risk preference is important as social norms may prescribe behaviours that may be in conflict with risk-aversion (Attanasio *et al.*, 2012). For example, Pirinsky (2012) found that risk-aversion tends to restrict deviant behaviour among households in a group. If risk-aversion affects a household's ability to abide by the set of group norms, then the adoption decision of a given set of technology among households may vary depending on the type of social capital they have. It can be argued that risk-aversion and social capital may have either synergetic or antagonistic effects for technology

adoption. When risk-aversion and social capital have synergetic effects, both factors will reinforce each other. However, when antagonistic effects are expected, the adoption decision depends on how strong the effects of social capital and norms are relative to the risk-aversion of individual households towards adoption.

As aside, we expanded the scope of the paper by considering access to formal credit. This access is quite instrumental in relaxing the liquidity requirements necessary to make investments in land management practices<sup>29</sup>. Most formal credit markets, however, systematically exclude the poorest households (Bhattamishra and Barrett, 2010). In the absence of formal credit markets, the poorest of the poor may therefore rely on their social capital to relax financial and labour constraints. In fact, Di Falco and Bulte (2013) suggested the existence of substitution effects between social capital and access to formal credit markets for the case of poor rural households in Ethiopia.

The paper is organized as follows: in section 4.2, we briefly discuss the effects of social capital on innovation adoption. Section 4.3 and 4.4 presents the study area along with the data sources and the methodology applied. Section 4.5 and 4.6 presents our findings and discusses the relevance of social capital for technology adoption. Section 4.7 concludes with a list of open questions and an outlook on next research topics.

# 4.2 Social capital and innovation adoption

Many attempts have been made to explain observed patterns of innovation adoption in smallholder agriculture (Groom *et al.*, 2011; Suri, 2011; Gebremedhin and Scott, 2003; Bewket, 2007; Kassie *et al.*, 2012; Abdulai and Huffman, 2014; Abdulai *et al.*, 2008). Studies in Ethiopia for example, suggest that adoption of land management practices and especially soil and water conservation measures are profitable (Kassie *et al.*, 2010; Kassie *et al.*, 2008; Benin, 2006; Pender and Gebremedhin, 2006). Yet, adoption rates of such profitable land management practices remain critically low (Shiferaw *et al.*, 2009; Di Falco and Bulte, 2013), which raises the question of why adoption rates of profitable technologies would not become much higher.

Studies based on individual economic incentives consider profitability as the major determinant of technology adoption and examine the factors that affect profitability of

<sup>&</sup>lt;sup>29</sup> Even though most land management practices are labor intensive, access to credit helps them to relax their cash constraints for hiring labor.

new technologies. From this point of view, the main determinants of innovation adoption are: information barriers (Foster and Rosenzweig, 1995; Munshi, 2004; Rosenzweig, 2010; Young, 2009; Conley and Udry, 2010; Abdulai *et al.*, 2008), supply-side constraints such as limited availability of credit (Shiferaw *et al.*, 2008; Coady, 1995; Croppenstedt *et al.*, 2003; Suri, 2011), differences in agro-ecological and climatic conditions (Deressa *et al.*, 2009), as well as heterogeneity among farm households in terms of adoption costs (Berger, 2001; Schreinemachers *et al.*, 2009; Schreinemachers *et al.*, 2010; Suri, 2011). This suggests that when adoption is considered as an individual action problem beyond profitability, capturing supply side constraints and market inefficiencies is important since affordability is crucial in explaining low adoption rates of profitable technologies (Shiferaw *et al.*, 2009; Abdulai and Huffman, 2014). As a consequence, it is necessary to consider the adoption decision as one that complements individual calculations of profitability with the ability to implement adoption practices successfully.

However, most adoption studies on land management practices with a focus on economic incentives pay little attention to the role of social capital<sup>30</sup>, generally defined as the networks, associations, institutions, degree of trust, norms and values that govern interactions among people (Collier, 2002; Grootaert, 2002). Even though some of the innovation adoption studies that consider information barriers capture the effect of social capital implicitly, they tend to concentrate on how the individual learning behaviour of households affects innovation adoption and diffusion rather than the amount and type of social capital these households possess. As a consequence, studies explicitly capturing the role of social capital generally found a statistically positive and significant effect on innovation adoption in agriculture (Isham, 2002). This shows the importance of focusing on how varying social capital drives adoption above and beyond individual learning behaviours.

In the absence of well-functioning formal labour, credit and information markets, social capital may enhance the adoption of agricultural innovations in many ways: First, it may help individual adopters to overcome their labour resource constraints, for example with labour-sharing arrangements (Krishna, 2001). This is especially the case

<sup>&</sup>lt;sup>30</sup> Grootaert, et al, 2002, classifies social capital into structural and cognitive aspects. Structural social capital is a relatively objective and externally observable construct while the cognitive aspects of social capital are more subjective and intangible concept.

when isolated individual efforts to solve supply side constraints of adoption are not feasible (Shiferaw *et al.*, 2009; Swinton and Quiroz, 2003; Nyangena, 2008). Second, it further enhances adoption by providing access to informal financial resources that may relax the farmers' cash constraints. This particular role of social capital is especially crucial, as the cash outlays needed to make investments in land management practices may make adoption unaffordable for poor farm households. Third, social capital facilitates the flow of information by reducing asymmetric information and transaction costs for innovation adoption, thereby reducing information market inefficiencies (Rogers, 1995; Abdulai *et al.*, 2008). For example, households who do not have access to formal extension services may learn about new technologies from their peer networks, as they share information with each other (Kassie *et al.*, 2012). Lack of social capital as such may therefore hinder adoption of profitable technologies when individual adopters have limited access to formal labour, capital and information markets<sup>31</sup>. On the other hand, social capital could potentially depress adoption rates by imposing a sharing obligation of benefits from adoption (Di Falco and Bulte, 2013).

Table 4.1 lists the possible limiting factors of profitable land management practices along with the expected effects of social capital<sup>32</sup>. Specifically, we hypothesize that when lack of credit, labour and information are limiting factors for adoption, social capital will have a positive effect on adoption by relaxing cash, labour and information constraints that a given farmer faces when making investments in new land management practices. We further hypothesize that when insurance markets are absent or inefficient, social capital enhances adoption by reducing uncertainty about new technologies (Abdulai *et al.*, 2008). Finally, we expect social capital to have a negative effect when individual adopters have to share the benefits from adoption but bear the investment costs of adoption<sup>33</sup>.

<sup>&</sup>lt;sup>31</sup> Note that social network structures might determine the specific market regimes (formal, informal and autarkic) of individual farmers (Henning et al. 2012). In line with this, Mawejje and Holden (2014) further documented that social network capital has significant positive effects on the ability of households to receive higher prices for coffee. Hence, observing the specific market regimes of an individual farm is potentially informative regarding the level of social capital.

<sup>&</sup>lt;sup>32</sup> This is not an exhaustive list of all the possible determinants of adoption. It only considers limiting factors for adoption that can be reduced through social capital.

<sup>&</sup>lt;sup>33</sup> We thank an anonymous referee for pointing this out.

Adoption decision	Limiting factors	Expected capital	effects	of	social
Individual adoption decision	Limited access to formal credit markets	Positive			
	Limited access to formal labour markets	Positive			
	Limited knowledge and information	Positive			
	Large uncertainty about returns	Positive			
	Low incentives for collective sharing of benefits	Negative			
Collective adoption decision <sup>34</sup>	Potential free-riding problems(public good)	Positive			

Table 4.1: Adoption decision and the role of social capital

The main contribution of this article is therefore to fill the research gap on social capital and agricultural technology adoption by investigating the differential effects of the type and size of social capital on technology adoption across households marked by different levels of risk-aversion. To the authors' knowledge, this study is the first to explore causal relationships between innovation adoption and social capital using a nationwide household survey that accounts for rich data both on social capital and risk preferences.

# 4.3 Data source and estimation strategy

### 4.3.1 Data sources

We used data from the 2004 and 2009 rounds of the Ethiopian Rural Household Survey (ERHS)<sup>35</sup>, the most comprehensive data set available for rural Ethiopia (ERHS, 2011). The data was collected by Addis Ababa University in collaboration with the International Food Policy Research Institute (IFPRI) and the Oxford University Center for African Economies. It covers fifteen Peasant Associations (PA) in four major administrative regions (Tigray, Amhara, Oromia and SNNPR) of the country. The ERHS interviewed 1,477 households seven times between 1989 and 2009. We make

<sup>&</sup>lt;sup>34</sup> In this manuscript, we did not considered such adoption decisions

<sup>&</sup>lt;sup>35</sup> This data has been made available by the Economics Department, Addis Ababa University, the Centre for the Study of African Economies, University of Oxford and the International Food Policy Research Institute. Funding for data collection was provided by the Economic and Social Research Council (ESRC), the Swedish International Development Agency (SIDA) and the United States Agency for International Development (USAID); the preparation of the public release version of these data was supported, in part, by the World Bank, AAU, CSAE, IFPRI, ESRC, SIDA and USAID.

use of the 2004 and the 2009 rounds of the ERHS, since social capital measurements, on which our analysis is based, are only included in these survey rounds. Unfortunately, risk preference measurements and the variables used to construct the social capital variable labelled 'connections to local authorities' are only included in the 2009 survey rounds. Due to missing values for some covariates, our effective sample constitutes 1141 households for 2009 and 917 households for 2004. The data set contains detailed information on household characteristics, agricultural production systems, food consumption patterns, production and marketing, and social capital variables, as well as experiments for risk and time preference.

Table 4.2 presents the list of improved land management practices included in our analysis along with the current rates of adoption<sup>36</sup>. We considered different soil conservation and water harvesting technologies together as a measure of adoption of improved land management practices. All the conservation techniques reported in Table 2 help to enhance soil organic matter contents, reduce soil erosion without yield reductions and enhance the capacity of the soil to hold water (Kassie *et al.*, 2012). We created a dummy variable as a measure of adoption of land management practices that takes a value of one if the household undertakes at least one of the mentioned practices in their plot and a value of zero if none of the practices are implemented.

Type of land management strategy	Adoption rates (2004)	Adoption rates (2009)
Stone bunds indigenous	22.5%	28.6%
Soil bunds indigenous	13.2%	27.7%
Stone bunds introduced	3.96%	4.7%
Soil bunds introduced	2.13%	5%
Fanyajuu	0%	0.25%
Contour ploughing	4.7%	10.7%
Strip conning	0.2%	1.1%
Alley cropping	0.2%	1.34%
Water harvesting	24.9%	11%

Table 4.2: List of land management strategies

Source: Own calculation from ERHS data

#### 4.3.2 Social capital variables

Empirical studies have used various ways of measuring social capital, for example through measuring local links quantified by membership in local informal networks

<sup>&</sup>lt;sup>36</sup> Note that some farmers have adopted multiple land management strategies.

(Narayan and Pritchett, 1999). Other variables used are connections to local organizations, the level of trust, the size of local and non-local kinship, as well as the level of perceived support at the time of hardship. In our analysis, social capital measures include the following aspects: i) membership in local informal saving and credit organizations; ii) membership in informal labour sharing arrangements; iii) membership in funeral insurance arrangements; iv) connections to local authorities; v) perceived trust towards others and vi) the number of relatives from both within and outside the village that the household knows and could depend on at times of hardship.

# *i.* Membership in local informal saving and credit organizations

This form of social capital is derived from information about membership in informal savings and credit organizations known locally as *Iquib*. It is an informal local association where members pay a periodically fixed contribution and receive the full amount of the contributed money on a rotational basis (Di Falco and Bulte, 2013). However, these arrangements are usually altered in response to individual needs for financing investments (Bhattamishra and Barrett, 2010). As explained in Table 1, membership to informal credit and saving associations facilitates adoption by providing access to informal financial resources that may relax the farmers' cash constraints<sup>37</sup>. We therefore expect a positive relationship between membership to informal credit and saving associations and adoption of sustainable land management strategies.

#### *ii.* Membership in informal labour sharing arrangements

This aspect of social capital captures labour sharing arrangements because of their relevance for the adoption of improved farmland management practices. In rural Ethiopia, farm households are usually organized in a labour exchange arrangement known as *Debo and Wonfel* in order to alleviate labour shortages, a very critical component in the adoption of improved land management practices. Membership in labour sharing arrangements facilitates the adoption of land management practices by

<sup>&</sup>lt;sup>37</sup> By reducing asymmetric information and transaction costs, it also plays a crucial role in disseminating information especially for smallholder and resource-poor farmers, whose information needs are usually not addressed by formal extension services. However, this function is secondary and we do not aim to capture such effects.

providing labour-exchange options (See Table 4.1). We expect a positive relationship between adoption and this form of social capital.

#### *iii.* Membership in funeral insurance arrangements

This particular social capital variable is measured from the participation of an informal arrangement locally known as *Iddir*. Iddirs' are established for providing mutual aid to families following the death of members (Di Falco and Bulte, 2013; Dercon *et al.*, 2006). They also serve as an insurance mechanism by providing money in case of accidents, such as fire, loss of livestock, harvest failure and during times of illness of members. This measurement of social capital is in line with the methods employed by Narayan and Pritchett (1999), who measured social capital by accounting for individual memberships to groups.

Potentially, this form of social capital may enhance adoption by improving knowledge and information about new land management practices. Iddir members typically meet once or twice a month, making a small payment into a group fund. For example, as of the 2009 survey round, about 35% and 29.1% of the respondents joined *Iddir* to participate in social activities and to make contacts respectively. Frequent interactions among *Iddir* members will most likely increase access to information, as members are likely to share knowledge and information. However, membership in funeral insurance arrangements potentially obstructs technology adoption, as households are expected to make significant cash and labor contributions for funeral expenses and other social commitments, potentially diverting financial resources away from agricultural innovation. It is worth mentioning that by providing credit, *Iddir* plays a crucial role in solving the liquidity problem facing households. However, credit provided by these institutions is usually strictly tied to funeral spending and illness. We therefore expect a negative relationship between adoption and this form of social capital, especially when lack of credit and labour rather than inadequate information and knowledge are barriers for adoption.

### iv. Connection to local authorities

This component of social capital is measured through network-based connections to local administration and government agencies. Connection to local authorities is measured by a dummy variable that takes a value of one if (i) the head of household holds an official position in the *Kebele*<sup>38</sup>or, (ii) if the parents of the head of household hold official positions in the *Kebele* or (iii) if close associates (relatives, not parents), friends and patrons hold an official position in the *Kebele*. This form of social capital can provide households in Ethiopia with access to formal and informal local level support, information dissemination and assistance for addressing other supply side constraints of adoption. Hence, we expect positive relationship between connections and adoption.

### v. Trust towards others

Trust is measured based on the respondent's perception of trustworthiness of people in the village. Trust in people is captured as a dummy variable with a value of one if respondents think that people in general are trustworthy and zero otherwise. This form of social capital enhances technology adoption as farm households may learn about new technologies from their networks that they most trust. As a result, we expect a positive relationship between adoption and this form of social capital.

# vi. Relatives

This form of social capital captures the local and non-local interactions and connections of the household among kin members. It reflects the self-reported relationships with relatives whom a given household considers to be very important in times of hardship, from both within and outside the village. It should be stressed that extending this component non-locally is quite novel compared to the existing literature, as considering relatives living outside the village has important implications for technology adoption. One can argue that relatives living far away have a far less influence on adoption rates compared to relatives living in the same village since financial ties are presumably less strong. However, geographically dispersed kin members usually share very different experiences and practices and hence the probability of learning something 'new' is very high (Wossen *et al.*, 2013).

We hypothesize that households with a relatively large number of relatives are less likely to adopt new technologies due to low incentives for collective sharing of benefits from adoption (Di Falco and Bulte, 2013; Baland *et al.*, 2011). In particular, compulsory sharing

<sup>&</sup>lt;sup>38</sup> Kebele is the lowest administrative level in Ethiopia.

and family tax may invite free riding behavior among kin members by attenuating incentives for hard work, as adopters are forced to share the rewards of their investment to their kin (Di Falco and Bulte, 2013; Di Falco and Bulte, 2011). Sharing benefits from adoption therefore introduces a social dilemma within the kin network as every individual member realizes that the benefits of adoption will have to be shared with others in the kin network (Di Falco and Bulte, 2013). However, having a large number of relatives may enhance adoption by channeling information and redistributing financial assets within kin members to make investments in land management strategies (Kassie *et al.*, 2012). As a result, when the adverse incentive effects of kinship are sufficiently strong, we expect a negative relationship between having large number of relatives and adoption of sustainable land management strategies.

#### 4.3.3 Risk preference variables

The effect of risk-aversion on technology adoption is well documented. As mentioned in the introduction, while the current empirical research on technology adoption focuses on the link between technology adoption and risk-aversion, this paper examines whether the effects of social capital on the adoption of improved land management practices are consistent across households with heterogeneous risk attitude levels.

In the experimental economics literature, it is becoming common to elicit individual risk preferences using field experiments. To this end, we used the risk preference experiments conducted by IFPRI in all of the ERHS villages of Ethiopia following the design developed by Binswanger (1980). The experiment considered a hypothetical decision for the amount of price-risk an individual is willing to take at the time of selling grain output. In the experiment, each choice set consisted of a pair of good and bad outcomes, each with a 50% probability. In each successive choice sets, the expected gain and standard deviation (spread) increased. Following Binswanger (1980) and Yesuf and Bluffstone (2009), risk-aversion coefficients were calculated using a Constant Partial Risk Aversion (CPRA)<sup>39</sup> utility function of the form:

$$U = (1 - r)Y^{1 - r}$$
(1).

<sup>&</sup>lt;sup>39</sup> Constant partial risk-aversion gives a fixed measure of risk-aversion that does not vary with wealth levels.

Where r is the constant partial risk-aversion coefficient and Y is the certainty equivalent of the prospect. The end points of the constant partial risk-aversion coefficients implied by each possible choice sets are presented in Table 4.3. Using these coefficients, we then grouped households into different levels of risk-aversion categories. We believe that the use of price-risk aversion fairly represents risk aversion towards the adoption of agricultural technologies, especially since profitability is the major factor of adoption. However, the use of price-risk aversion might also potentially be a flawed measure of technology adoption since preferences for risk are likely to be domain specific (Hansson and Lagerkvist, 2012).

Table 4.3: Basic structure of the risk experiment

Choice	Risk category	CPRA	Percent of subjects (%)
1	Severe	3.25 to $\infty$	9.2
2	Intermediate	1.1 to 3.25	13.6
3	Moderate	0.68 to 1.1	24.7
4	Slight to neutral	0.33 to 0.68	18.3
5	Neutral to risk loving	0 to 0.33	34.2

### 4.4 Empirical strategy

Following Abdulai *et al.* (2008); Abdulai and Huffman (2014) and Suri (2011), we assumed that a particular farm household would consider implementing new land management practices if the expected benefit from adoption is higher than from non-adoption. Empirically, the decision to adopt a given land management practice or not is estimated using a probit model specification:

$$Y_{h}^{*} = \beta_{0} + \gamma X_{h}^{'} + \vartheta Z_{h}^{'} + \mu_{h}$$

$$\tag{1}$$

For the latent variable  $Y_h^*$ , the estimation is based on the observable binary discrete choice of whether the farmer adopted and implemented improved land management practices or not.

$$Y_h = \begin{cases} 1ifY_h^* > 0\\ 0, otherwise \end{cases}$$
(2).

Where,  $X'_h$  includes access, institutional, plot and household characteristics while  $Z'_h$  includes social capital variables.  $Y_h$  is a dummy variable measuring whether the farm households had adopted land management strategies and  $\mu_h$  is household specific error

term.  $\gamma$  and  $\vartheta$  are vector of parameters to be estimated. The underlying assumption is that, a farmer will consider adoption ( $Y_h = 1$  over non-adoption ( $Y_h = 0$ ) if the expected benefit from adoption is higher than the expected benefit from non-adoption.

We tested different econometric model specifications to estimate the effects of social capital on adoption decisions of improved land management practices. First, in order to analyze the effect of social capital across households with heterogeneous risk taking behaviour, we estimated a probit model using cross-sectional data from the 2009 survey round where data on risk taking behaviour is readily available.

Second, in the estimation procedure, we controlled for the endogeneity problem posed by social capital variables  $(Z'_h)$  using an instrumental variable regression approach. Social capital variables are considered to be endogenous since wealthier households might have more opportunities to possess more social capital compared to poorer households. Moreover, households with better social capital might own lands with excellent soil quality, which in turn affects the adoption of land management practices (Di Falco and Bulte, 2013). In this case, membership in local informal saving and credit organizations, membership in informal labour sharing arrangements, membership in funeral insurance arrangements and the level of connections to local authorities as well as the choice to adopt land management techniques are simultaneously determined based on specific farm characteristics<sup>40</sup>. This could lead to a reverse causation between the level of social capital that households have and the individual decision to adopt land management practices. Following Abdulai et al. (2011) and Di Falco and Bulte (2013), we therefore considered social capital variables  $(Z'_h)$  as endogenous in Eq. (1) above. The determinant of social capital formation is then specified as follows:

$$Z_{h}^{'} = \alpha_{0} + \theta X_{h}^{'} + \delta W_{h}^{'} + \varepsilon_{h}$$
(3).

Where  $W'_h$  is a vector of instruments that are correlated to social capital, but not with the error term of the adoption model. In order to find appropriate and relevant instruments for our social capital variables, we explore community and historical characteristic following Glaeser *et al.* (2002). One factor that is closely related to the formation of *Iddir* in the Ethiopian context is having experienced death shocks in the

<sup>&</sup>lt;sup>40</sup> We thank an anonymous referee for pointing this out

past (Dercon *et al.*, 2006). We therefore considered idiosyncratic death shocks in the household (experiencing death of a family member in the past five years) as a potential instrument for *Iddir*. This variable is directly correlated with the formation of *Iddir* network but is unlikely to be directly correlated with the propensity to adopt new land management techniques (one can argue that experiencing death shocks may not be exogenous as it affects labour supply and hence adoption, however we controlled for household size and our test statistics support the idea that it helps to strengthen our case). Demeke (2010) confirmed that people who were born and raised in the same village tend to have more extensive social interactions and are characterized by stronger social ties. We therefore used the dummy variable of whether the household head was born in this village or not as a candidate instrument, as people who lived together for a long time form *Iquib* mainly with the intent of relaxing their financial constraints. We assume here that this variable is directly correlated with the formation of *Iquib* networks, but is unlikely to be directly correlated with the decision to adopt new land management techniques.

Since the decision to join a labour sharing arrangement depends on the availability of labour capacity, we used temporarily migration decision of adult members (excluding the household head, as migration of the household head might affect adoption decision) as an instrument. In particular we created a dummy variable using the following question from the survey: "*Did any members of the household who are 15 Years of age or older temporarily migrate to a place outside this village*?" We hypothesize that temporary migration of adult members will affect the decision to join labour sharing arrangements, but not the decision to adopt new land management techniques. Finally we used the variable whether the parents of either the head or the spouse are important in the traditional social system as a potential instrument for the variable connection to local authorities. This variable is closely related to the formation of local political and institutional connections, but not with the adoption decision.

Given that the endogenous social capital variables are binary, one can employ 2SLS as well as the Smith and Blundell (1986) approach to correct endogeneity bias. Since we employ a probit model specification, 2SLS is a way of estimating the linear probability model (LPM). However, Abdulai *et al.* (2011) have shown that the Smith and Blundell

(1986) approach is consistent while using a probit specification. As a result, we used the Smith and Blundell (1986) approach to correct endogeneity bias in our model specification. In this approach, we first ran the first stage separately and used the residuals in the second stage to correct for endogeneity. This procedure of inserting first stage residuals in the main model is in the spirit of the Wu–Hausman technique (Wooldridge, 2002; Di Falco and Bulte, 2014; Abdulai *et al.*, 2011). The endogeneity correction model is then specified as follows:

$$Y_{h}^{*} = \beta_{0} + \gamma X_{h}^{'} + \vartheta Z_{h}^{'} + \varphi R_{h}^{'} + \mu_{h}$$
(4).

Where  $R'_h$  is a vector of residuals from in Eq. (3) above.

Third, using panel data, we implement a random-effect probit model. The randomeffect specification assumes that the error term is not correlated with the predictors, which allows for time-invariant variables to play a role as explanatory variables. However, the random-effect specification is not without drawbacks, as violation of the exogeneity assumption leads to biased parameter estimates (Wooldridge, 2002; Bezabih and Sarr, 2012). Theoretically, the standard fixed-effect model would therefore be a better option, as it controls for all time-invariant differences between households (Wooldridge, 2002). However, standard fixed-effect models cannot be used to investigate time-invariant causes of adoption (this is a drawback in our case since there is little variation in our social capital and other explanatory variables over time, and since estimates of risk preference parameters are only available for the last round). As a result, we only present fixed-effect logistic regression results as a robustness check.

In addition to standard fixed-effect estimation procedures, we implemented a pseudofixed-effect model, in which a random-effect model is ran while simultaneously controlling for unobserved heterogeneity by adding the mean values of time-varying explanatory variables in an auxiliary regression in order to account for the possible correlation of time-invariant unobserved heterogeneity with observed covariates<sup>41</sup>. Following Mundlak (1978) and Di Falco and Bulte (2013), we included the mean values of the time-varying covariates in an auxiliary regression as follows:

<sup>&</sup>lt;sup>41</sup> A pseudo-fixed-effect model is estimated instead of a standard fixed-effects model, because most of the social capital indicators do only rarely change over time and hence their impact on adoption might be not adequate captured applying a standard fixed-effects approach.

$$\mu_h = \alpha \acute{x} + \omega_h, \omega_h iid(0, \delta_w^2) \tag{5}.$$

Where x is the means of the time-varying explanatory variables within each household (cluster mean), a is the corresponding vector coefficient, and  $\omega_{h}$  is a random error unrelated to x.

Fourth, since plot-level characteristics may become significant determinants of adoption decision, we estimated the adoption decision at plot level. To account for the possible correlation of plot-invariant unobserved heterogeneity with observed covariates, we implemented a pseudo fixed-effect model, in which we ran a random-effect model while simultaneously controlling for unobserved heterogeneity by adding the mean values of plot-varying explanatory variables.

# 4.5 Descriptive statistics

Definitions and descriptive statistics for social capital, plot characteristics, household characteristics as well as other variables used in the regression analysis are given in Table 4.4. As described above, social capital, the main objective of this study, is measured by membership in local informal saving and credit organizations, membership in informal labour sharing arrangements, membership in funeral insurance arrangements, connection to local authorities, trust towards others and the number of relatives. Membership in local informal saving and credit organizations (*Iquib*) remains fairly constant over time (19% in 2004 compared to 24% in 2009). Likewise, membership in informal labour sharing arrangements shows an increasing trend over time (50% in 2004 compared to 66% in 2009). Membership in traditional funeral associations (*Iddir*) increases marginally from 81% to 85%. The Spearman correlation coefficients among the social capital variables imply the existence of observable, albeit low, correlation confirming that the above variables measure distinct aspects of social capital<sup>42</sup>.

We also included household characteristics such as age, household size and educational attainment levels. The average age of the household head is 51.8 and 54.5 years in 2004 and 2009, respectively. Similarly, the average household size did not

<sup>42</sup> The highest correlation among the social capital measures is between the number of relatives and membership to Iddir (Spearman correlation coefficient =-0.36 p =0.0000) followed by Iddir and labor sharing membership (Spearman correlation coefficient = 0.24 p = 0.0000).

show significant changes over time (5.8 in 2004 compared to 5.9 in 2009). In addition, we included institutional and access variables such as access to credit, access to production safety net programs and access to extension because of their relevance for adoption. Farm specific characteristics such as soil fertility and slope, which show the vulnerability of fields to the erosion problem, were captured. The inclusion of these variables is based on economic theory and empirical literature on the adoption of land management practices.

Table 4.4: Variable list and descriptive statistics

	2009		2004	
Variable	Mean	SD	Mean	SD
Demographic characteristics				
Household size (Family size in numbers)	5.9	2.48	5.8	2.43
Age (Age of the household head in years)	54.5	15.3	51.8	15.3
Education (1= household head is literate)	0.53	0.49	0.37	0.48
Assets and resource constraints				
TLU (Livestock herd size in tropical livestock units)	4.2	25.9	2.84	2.89
Farm size, (in hectares)	0.4	1.15	1.6	1.9
Non-food expenditure(monthly expenditure on non-food items	245.6	313.7	109.6	161.5
in birr)				
Soil fertility (the level of soil fertility <sup>43</sup> 1=Lem, 2=Lem-Tef,	1.57	0.58	1.61	0.61
3=Tef)				
Fertilizer use (1= the household uses fertilizer)	0.66	0.47	0.54	0.49
Slope of field(Type of slope 1= flat, 2= medium=step)	1.27	0.39	1.29	0.44
Land tenure <sup>44</sup> (1= has tenure security)	0.85	0.35	0.53	0.49
Access Variables				
Access to safety nets(1= has access to safety net)	0.17	0.38	0.43	0.49
Access to credit (1= has access to credit)	0.51	0.5	0.46	0.49
Access to extension (1= has access to extension)		0.49	0.22	0.41
Social capital Variables				
Iquib(1= member to Iquib)	0.24	0.42	0.19	0.39
Connection to local authorities (1= has connections)	0.54	0.49		
Labor sharing(1=member of labor sharing arrangements)	0.66	0.47	0.50	0.5
Iddir(1= member to Iquib)	0.85	0.35	0.81	0.39
Relatives(Number of relatives in and outside the village)	2.83	1.98	2.4	1.9
Trust(1=Trustworthy)		0.5	0.33	0.46
Other variables				
Climate shocks <sup>45</sup> (1=has experienced climate shock in the past)	0.75	0.43	0.79	0.40
Early adopters(Number of previous adopters in the village)	45	29	29	19
Risk aversion (1= risk averse)	0.66	0.47		

<sup>&</sup>lt;sup>43</sup> Lem, Lem-Tef and Tef refers to fertile, moderate and infertile soil quality respectively

<sup>&</sup>lt;sup>44</sup> Land tenure security is attained when the land is officially registered and the household has the right to transfer the land

<sup>&</sup>lt;sup>45</sup> Climate shock refers to the occurrence of drought, too much rain or flood and frosts or hailstorm in the last five years.

#### 4.6 Results

Table 4.5 shows the results of our regression analysis using cross-sectional data from the 2009 survey round. Model 1 is a parsimonious specification that includes only standard controls for adoption. We then controlled for social capital variables along with standard controls of adoption (Model 2). Model 3 presents the results of the IV probit specification in which we instrumented the social capital variable connection to local authorities, membership in labour sharing arrangements, membership in informal local saving and credit association(*Iquib*) and membership in funeral insurance arrangements(*Iddir*). Finally, Model 4 presents the alternative estimates of the IV pseudo fixed-effect model at plot level. Table 4.6 presents results using panel data from the 2004 and 2009 survey rounds. Table 4.7 presents regression results on the effects of social capital across households differentiated by the level of formal credit access. Table 4.8 shows the results of the interaction effect between risk-aversion and social capital. Finally, Table 4.9 and 4.10 present alternative fixed-effect logistic regression and order-probit model results as a robustness check, respectively.

Model 1 in Table 4.5 shows the results of the baseline specification where we included household characteristics, risk aversion, access to credit, wealth (income) indicators and other standard controls for adoption. To capture the wealth (income) effect we included TLU (total livestock endowment in tropical units), farm size and expenditures on non-food items. The result reveals that most of the standard controls have the expected effects. In particular, we found that both access to formal credit and risk aversion play a significant role in adoption decision. Model 2 further presents a parsimonious specification, where we introduced social capital variables in addition to the standard controls. Our result underscores that social capital is a significant factor for adoption. However as mentioned before, membership in local informal saving and credit organizations, membership in informal labour sharing arrangements, membership in funeral insurance arrangements and the level of connections to local authorities as well as the choice to adopt land management techniques might be

simultaneously determined and hence may become endogenous. The discussion of results is therefore based on IV probit model (Model 3 in Table 4.5)<sup>46</sup>.

The average marginal effects of membership in informal local saving and credit association (*Iquib*) and membership in labour sharing arrangements were found to be 0.194 and 0.40 respectively. Switching from non-member to membership in a local saving and credit association (*Iquib*) increases the probability of adopting improved land management practices by 19.4%. The result confirms that by relaxing the liquidity problems of poor households, membership in local informal saving and credit associations (*Iquib*) enhances adoption of improved land management practices. The marginal effect of membership in labour sharing arrangements is also positive and significant. The result underscores that membership in labour sharing arrangements practices by relaxing labour resource constraints.

For the other measures of social capital, namely relatives (kinship) and membership in funeral insurance arrangements (*Iddir*), we found significant negative impacts on the probability of adopting improved land management practices. The adverse effect of kinship on adoption implies that compulsory sharing and strong loyalty among kin members compromises the benefits from land management investments, leading to free-riding behaviour among kin members. Since the effect of membership in funeral insurance arrangements (*Iddir*) on technology adoption has not been explicitly addressed before, we cannot make comparisons with other studies. However, our result is not surprising since membership in *Iddir* implies significant financial and labour contributions for handling burials, which can by no means be considered investments. Finally, connection to local authorities is found to be positive and significant. The result is as expected since this type of social capital provides households access to formal and informal local institutional support to make investments into land management strategies.

According to our estimation, the larger the number of pervious adopters in the village, the higher would be the probability of adopting land management practices. The result

<sup>&</sup>lt;sup>46</sup> The residuals in the second stage are not significant implying that the parameters were estimated consistently (for a similar procedure, see Abdulai *et al.*, 2011, pp1419-1420). See the first stage estimation results in Table 4.11 in the appendix at the end of this chapter.

supports the evidence that farmers learn about technologies from their peers<sup>47</sup>. Rogers (1995); Di Falco and Bulte (2013); Conley and Udry (2010); Bandiera and Rasul (2006); and Munshi (2004) have reported similar results. In terms of other institutional variables, access to production safety net is found to have a positive and significant effect on the adoption of land management practices. This result is as expected since efficient utilization of water and expansion of small and medium scale irrigation, as well as water harvesting during rainy seasons for use in the dry months, is at the core of the Ethiopian safety net program. Moreover, access to the production safety net program assist individual households to acquire the necessary cash and in-kind supports needed to acquire storage tanks for water harvesting. Finally, Model 4 in Table 4.5 provides the estimates of the elaborate plot level models after controlling for pseudo-fixed effects. Since all farmers have multiple plots, the sample size of the analysis increases to 5754. We found similar results for our social capital variables both in terms of the magnitude and the direction of effects.

<sup>&</sup>lt;sup>47</sup> Our estimation does not allow for examining how the learning process takes place. For empirical and methodological approaches of learning effects, we suggest studies such as Conley and Udry (2010); Bandiera and Rasul (2006).

	Probit IV Probit		IV Prohit	IV pseudo FE	
	(1)	(2)	(3)	(4)	
Household level				Plot level	
Household size	0.006	0.0064	0.0005	-0.0045	
	(0.0000)	(0.0039)	(0,000)	(0.0018)	
Age	-0.0024	-0.0015	-0.0014	0.0033	
1.50	(0.0045)	(0.0034)	(0.0034)	(0.0034)	
$Age^2$	0.00002	0.000013	0.00001	-0.000017	
	(0,00004)	(0,00003)	(0,00003)	(0,00003)	
Education	0.053**	0.028	-0.014	-0.044	
2000000	(0.022)	(0.018)	(0.037)	(0.0397)	
TLU	0.0029*	0.0011***	0.0017**	0.00085	
	(0.0015)	(0,0006)	(0,0007)	(0.00000)	
Farm size	-0.009**	-0.0085***	-0.0098***	-0.0091***	
	(0.0039)	(0.0029)	(0.0028)	(0,0034)	
Non-food expenditure	0.00015***	0.00006**	0.00006*	0.00004	
rion lood expenditure	(0.00019)	(0,00003)	(0.00003)	(0.00008)	
Soil fertility	0.053**	0.0135	0.0097	0.0099	
Son fertility	(0.023)	(0.019)	(0.0097)	(0.00)	
Fertilizer use	$0.109^{***}$	0.039*	0.0349	0.022	
i entilizer üse	(0.028)	(0.021)	(0.034)	(0.022)	
Slope of field	(0.020) 0.125 <sup>***</sup>	0.078***	0.078***	0.024)	
Slope of field	(0.039)	(0.078)	(0.073)	(0.051)	
I and tenure	0.011	0.008	(0.027)	-0.0026	
	(0.038)	(0.030)	(0.029)	(0.039)	
Access to safety nets	0.092***	$0.1002^{***}$	0.091**	0.088**	
recess to survey nets	(0.052)	(0.035)	(0.038)	(0.041)	
Access to credit	(0.03+7) 0.137 <sup>***</sup>	0.012	-0.0048	-0.067	
Access to creat	(0.027)	(0.012)	(0.038)	(0.0/3)	
Access to extension	(0.027)	0.0198	-0.0098	(0.0+3) 0.071 <sup>**</sup>	
Access to extension	(0.024)	(0.017)	(0.031)	(0.071)	
Iquib	(0.024)	(0.017) 0.104***	0.194	(0.0313) $0.473^{**}$	
Iquib		(0.026)	(0.194)	(0.235)	
Connection to local authorities		(0.020)	(0.190) 0.28*	0.266**	
connection to local authorities		(0.044)	(0.26)	(0.160)	
Labor sharing		(0.019)	(0.101)	0.528***	
		(0.025)	(0.120)	(0.136)	
Iddir		(0.023) 0.110***	(0.129) 0.146**	(0.130)	
Iddii		(0.041)	(0.065)	(0.075)	
Relatives		(0.041)	(0.005)	(0.073)	
Relatives		(0.0015)	(0.0017)	(0.005)	
Trust		(0.00+3)	(0.00+7)	(0.005)	
Trust		(0.023)	(0.018)	(0.028)	
Rick Aversion	0.162***	(0.021) 0.130***	(0.0209) 0.125 <sup>***</sup>	(0.0225) 0.112***	
RISK AVEISION	(0.02)	(0.016)	(0.026)	(0.035)	
Farly adopters	(0.020)	0.010	(0.020)	0.000	
Larry adopters	(0.007)	(0.004)	(0,0004)	(0.0040	
Climate shock	(0.0000)	(0.0004)	_0.0004)	0.0003)	
CHIHATE SHOCK	-0.027	-0.024	-0.023	-0.019/	
Number of observation	(0.020) 1141	(0.021) 11/1	(0.022) 11/1	(0.018)	
Form fixed offects	1141 No	1141 No	1141 No	5754 Vas	
Decudo D2	INU 0.29	1NU 0.52	INU 0.54	105	
r seudo K2	0.58	0.33	0.34	0.32	

Table 4.5: Effects of social capital using cross-sectional data from 2009

Village clustered standard errors in parentheses. \* indicates statistical significance at the 10% level\*\* significant at the 5% level, \*\*\* significant at the 1% level. Results are average marginal effects. For IV-Probit estimates, residuals from the first stage are included but not reported.

The foregoing results of our IV probit estimations were based on cross-sectional data from the 2009 survey round. As a result, we present regression results using panel data from the 2004 and 2009 survey rounds, where we had data on all aspects of standard controls, with the exceptions of connection to local authorities and risk-aversion. Table 4.6 shows the results of the random-probit and probit pseudo fixed-effects. The estimates of both models are numerically similar in terms of the magnitude and direction of the effects. Consistent with our previous findings, membership in informal local saving and credit association (*Iquib*) and membership in labour sharing arrangements have positive effects on the probability of adopting improved land management practices. Similarly, membership in funeral insurance arrangements (*Iddir*) has a negative effect on the probability of adopting improved land management practices.
	Pro	bit RE	Probit pseudo FE	
	(5)	(6)	(7)	
Household size	0.0085	0.013*	0.015	
	(0.007)	(0.007)	(0.015)	
Age	-0.0027	-0.0007	-0.0025	
-	(0.0058)	(0.0057)	(0.0065)	
Age <sup>2</sup>	0.00003	0.000012	0.00003	
C	(0.00005)	(0.00005)	(0.00005)	
Education	0.029	0.025	0.027	
	(0.034)	(0.0338)	(0.034)	
TLU	0.034***	$0.0265^{***}$	$0.024^{***}$	
	(0.065)	(0.0065)	(0.007)	
Farm size	-0.0135	-0.0097	-0.018	
	(0.012)	(0.013)	(0.049)	
Non food expenditure	0.00026***	0.0002***	0.0002**	
•	(0.00008)	(0.00008)	(0.00008)	
Soil fertility	$0.097^{***}$	$0.065^{**}$	-0.047	
2	(0.028)	(0.029)	(0.048)	
Fertilizer use	$0.105^{***}$	$0.114^{***}$	0.125***	
	(0.0367)	(0.037)	(0.038)	
Slope of field	0.248***	$0.248^{***}$	0.162**	
1	(0.042)	(0.043)	(0.071)	
Land tenure	0.033	0.032	0.043	
	(0.036)	(0.036)	(0.037)	
Access to safety nets	$0.086^{**}$	$0.062^{*}$	0.025	
Ş	(0.04)	(0.04)	(0.042)	
Access to credit	0.141***	0.104***	0.101*	
	(0.03)	(0.031)	(0.031)	
Access to extension	0.111****	0.096***	0.111****	
	(0.034)	(0.034)	(0.035)	
Iquib		0.086**	0.105****	
1		(0.03)	(0.04)	
Labor sharing		0.233****	0.246****	
6		(0.032)	(0.033)	
Iddir		-0.221***	-0.194***	
		(0.04)	(0.044)	
Relatives		-0.013	-0.012	
		(0.008)	(0.0083)	
Trust		0.036	0.039	
		(0.031)	(0.032)	
Early adopters	$0.013^{***}$	0.0120****	0.0059**	
• •	(0.0009)	(0.00095)	(0.002)	
Climate shock	0.040	0.021	0.020	
	(0.038)	(0.038)	(0.039)	
Year dummy	-0.055	-0.064	-0.011	
-	(0.041)	(0.042)	(0.013)	
LR $\chi 2$	11.99	6.09	7.36	
<i>P</i> value: Prob> $\gamma 2$	0.000	0.007	0.003	
Log likelihood	-885.8	-845.53	-831.17	
Number of observation	1834	1834	1834	

Table 4.6: Effects of social capital using panel data from 2004 and 2009

Robust standard errors in parentheses.\* indicates statistical significance at the 10% level\*\*

significant at the 5% level, \*\*\* significant at the 1% level.

Next, we examined the empirical question of whether social capital can be a substitute for formal credit by using the relevant interactions between credit and social capital as regressors (Table 4.7). In doing so, we analyzed whether access to formal credit markets crowds out the effects of social capital for technology adoption. We hypothesize that only households without access to formal credit tend to rely on their social capital to acquire the necessary financial and labour requirements in order to make investments in land management practices.

The result in Table 4.7 shows two important implications. First, the marginal effect of the interaction term between connection to local authorities and access to formal credit become positive and significant while the direct effect of connection to local authorities is positive albeit insignificant. This result suggests a possible synergetic effect between the social capital variable connection to local authorities and access to credit<sup>48</sup>.Similarly, the marginal effect of the interaction term between membership to labour sharing arrangements and access to credit becomes significant and negative while the direct effect of membership to labour sharing arrangements is positive, suggesting a possible substitution effect between the two variables. Being a member of labour sharing arrangement has a significant and positive effect on adoption of land management strategies. However, its positive impact declines when households gain access to formal credit. The result underlines that when access to formal credit is granted, labour constraints can be relaxed through hiring instead of joining labour sharing arrangements. Second, the interaction term between credit and membership in funeral insurance arrangements (Iddir) has a positive and significant effect on adoption while the effect of the constitutive term is negative and significant, implying a possible substitution effect between membership in funeral insurance arrangements (Iddir) and access to formal credit. The result underscores that expansion of formal credit schemes into rural areas allows individuals to avoid the disincentive effects of Iddir.

<sup>&</sup>lt;sup>48</sup> Note that, since the probit specification constitutes a nonlinear model, the interaction between social capital variables and access to credit cannot be evaluated simply by looking at the sign, magnitude, or statistical significance of the coefficient on the interaction term (Ai and Norton, 2003).

	IV Probit
	(8)
	All households
Household size	-0.0032
	(0.0046)
Age	-0.00085
	(0.0033)
Age <sup>2</sup>	0.0000006
	(0.000028)
Education	-0.0175
	(0.021)
TLU	0.0009
	(0.00063)
Farm size	-0.0067**
	(0.0027)
Non-food expenditure	0.00006**
	(0.000033)
Soil fertility	0.0017
	(0.021)
Fertilizer use	0.063
	(0.024)
Slope of field	0.073
	(0.025)
Land tenure	0.0089
	(0.026)
Access to safety nets	0.072
	(0.036)
Access to credit	-0.046
	(0.078)
Access to extension	0.003
T '1	(0.03)
Iquib	$0.358^{**}$
T. '1. Y	(0.169)
Iquib*access to credit	-0.040
Comparties to least with with a	(0.053)
Connection to local authornties	0.258
Compartien to local authorities *second to and it	(0.148)
Connection to local authornies "access to credit	(0.079)
Labor sharing	(0.055)
Labor sharing	(0.125)
Labor sharing * access to gradit	(0.123) 0.202***
Labor sharing access to credit	(0.054)
Iddir	0.302***
Iddii	(0.060)
Iddir*access to credit	0.185***
	(0.062)
Relatives	-0.0216**
Kelatives	(0.000)
Relatives*access to credit	0.016
	(0.010)
Trust	-0.013
11051	(0.036)
	(0.030)

Table 4.7: Access to credit and social capital effects using cross-sectional data from 2009

	IV Probit	
	(8)	
	All households	
Trust* access to credit	0.0397	
	(0.039)	
Risk Aversion	$0.101^{***}$	
	(0.0245)	
Early adopters	$0.0037^{***}$	
	(0.00034)	
Climate shock	-0.025	
	(0.022)	
Number of observation	1141	
Pseudo R2	0.56	

Village clustered standard errors in parentheses. \* indicates statistical significance at the 10% level\*\* significant at the 5% level, \*\*\* significant at the 1% level. Results are average marginal effects. Residuals from the first stage are included but not reported.

Finally, we present the differential effects of social capital on technology adoption across households having different levels of risk-aversion by analyzing the interaction effects of social capital and risk attitude variables. As mentioned in the introduction, some aspects of social capital, such as reliance on first-degree relatives, affect riskaversion positively. If risk-aversion affects the formation of links and networks, then the effect of social capital across households holding heterogeneous risk attitude levels could be very different. The aim of this analysis is therefore to examine whether the effects of social capital are robust across households with different levels of riskaversion. We tested this relationship using the coefficient of partial risk-aversion calculated from Table 4.3. We found that about 65.8% of households are risk-averse. Based on the results, we undertook a regression analysis by including social capital variables, risk-aversion coefficients and the interaction terms between social capital and risk-aversion coefficients in one regression. We hypothesize that risk-averse households tend to rely more on their social networks in making adoption decisions compared to risk-loving households. This hypothesis was tested using cross-sectional data from the 2009 survey round since risk measurements were available only in this round.

Table 4.8 presents our results. We found that the interaction terms between two of our social capital variables and risk-aversion are statistically significant. In particular, we found a significant and negative interaction term between membership in labour sharing arrangements and risk-aversion while the direct effect of membership in labour sharing arrangements is significant and positive for all households independent of their

risk attitude levels. Similarly, the interaction term between membership in funeral insurance arrangements (*Iddir*) and risk-aversion is positive while the direct effect of membership in funeral insurance arrangements (*Iddir*) is significant and negative for all households independent from their risk attitudes. The result supports our hypothesis that even though access to social capital impacts technology adoption, its effect is not similar across households holding different risk-aversion levels. The result also underscores the importance of incorporating individual risk preferences while analyzing the impacts of social capital on technology adoption. For example, joining associations like membership in funeral insurance arrangements (*Iddir*) is not equally important for risk-averse and risk-loving households.

	IV Probit
	(9)
Household size	-0.0029
	(0.0047)
Age	-0.0014
	(0.0036)
Age <sup>2</sup>	0.00001
	(0.00003)
Education	-0.012
	(0.036)
TLU	$0.0014^{**}$
	(0.00067)
Farm size	-0.0066**
	(0.003)
Non-food expenditure	$0.00005^{*}$
	(0.00003)
Soil fertility	0.0068
	(0.0212)
Fertilizer use	$0.0498^{**}$
	(0.023)
Slope of field	$0.079^{***}$
	(0.026)
Land tenure	0.0024
	(0.028)
Access to safety nets	$0.077^{**}$
	(0.038)
Access to credit	-0.0333
	(0.051)
Access to extension	-0.0037
	(0.030)
Iquib	0.291
	(0.182)
Iquib*risk aversion	0.1106***
	(0.043)
Labor sharing	0.419***
	(0.131)
Labor sharing*risk aversion	-0.234***
	(0.049)

Table 4.8: Risk aversion and social capital effects using cross-sectional data from 2009

	IV Probit
	(9)
Iddir	-0.265***
	(0.056)
Iddir*risk aversion	0.165***
	(0.044)
Relatives	-0.014**
	(0.0065)
Relatives*risk aversion	0.010
	(0.0105)
Trust	0.014
	(0.023)
Trust*risk aversion	-0.0064
	(0.037)
Connection to local authorities	0.292**
	(0.144)
Early adopters	0.0037***
	(0.00036)
Risk aversion	0.116***
	(0.040)
Climate shock	-0.0239
	(0.021)
Number of observation	1141
Pseudo R2	0.554

\* indicates statistical significance at the 10% level\*\* significant at the 5% level, \*\*\* significant at the 1% level. Results are average marginal effects. Residuals from the first stage are included but not reported.

#### 4.7 Robustness checks

In this section, we checked the robustness of our main results to alternative model specifications. In particular, we undertook a robustness check using the following specifications:

- 1) Fixed-effects logistic regression instead of random-effect probit models
- 2) Order-probit model to examine to what extent specific coding of our dependent variable impact the results
- Robustness of results while using the 5-point measure of risk-aversion and two categories (risk averse versus risk neutral to loving)

As mentioned in the methodology, we implemented a random-effect probit model of adoption due to limited within-individual differences in the data. However, as a robustness check we provide fixed-effect logistic regression results in Table 4.9. The effect of social capital remains the same while using a fixed-effect logistic model.

	Fixed effect logit
	(10)
Household size	0.0019
	(0.0043)
Age	-0.00076
-8-	(0.0028)
$\Delta \sigma e^2$	0.000007
nge -	(0.0003)
Education	0.0008
Education	-0.0000
	(0.0039)
ILU	(0.004)
	(0.098)
Farm size	-0.227
	(0.137)
Non-food expenditure	-0.000006
	(0.0005)
Soil fertility	-0.42
	(0.277)
Fertilizer use	$0.719^{*}$
	(0.385)
Slope of field	0.831**
•	(0.419)
Land tenure	$0.541^{*}$
	(0.288)
Access to safety nets	0.628*
	(0.369)
Access to credit	0.572***
	(0.213)
Access to extension	(0.213)
Access to extension	(0.260)
Iouih	(0.209)
Iquib	0.304
T - 1 1	(0.371)
Labor sharing	1.21
	(0.274)
lddir	-0.045
	(0.535)
Relatives	-0.198
	(0.075)
Trust	0.057
	(0.263)
Early adopters	$0.044^{***}$
	(0.0129)
Climate shock	0.0352
	(0.296)
Year dummy	-0.148
	(0, 109)
$I R \sqrt{2}$	156.7
$r_{\lambda^2}$	0.0000
$p$ value. 1100/ $\chi^2$	122.6
Lug inclinuou Number of chamistics	-122.0 590
number of observation	300

Table 4.9: Fixed effect logistic regression results

Robust standard errors in parentheses.\* indicates statistical significance at the 10% level\*\* significant at the 5% level, \*\*\* significant at the 1% level.

As our second robustness test, we examined the coding of our dependent variable. In our model specification, we considered nine different land management practices. We created a dummy variable that takes a value of one if the household undertakes at least one of the mentioned practices in their plot and a value of zero if none of the practices are implemented. In order to test the sensitivity of our results to the coding of our dependent variable, we considered a different specification and estimated an orderprobit model of adoption. We constructed the endogenous variable as an ordinal variable ranging from zero (i.e. the household has not adopted any of the land management practices) to nine (implying the household has adopted all the land management practices). Our results are presented in Table 4.10 (Model 11). The main implications and interpretations of our social capital variables remain unchanged while using order-probit model.

$(11)$ $(12)$ $(13)$ Household size $0.027^+$ $0.0068^+$ $0.0064$ $0.016$ $(0.0038)$ $(0.0039)$ Age $-0.064$ $-0.0015$ $-0.0015$ $Age^2$ $0.00007$ $0.00035)$ $(0.0034)$ $Age^2$ $0.00007$ $0.00001$ $0.000013$ Education $0.122$ $0.0249$ $0.028$ $0.018^+$ $0.0018^+$ $0.0011^{***}$ $0.0085)$ $0.0178)$ $(0.0183)$ Farm size $-0.008$ $-0.007^{***}$ $0.0009)$ $0.00006^+$ $0.00006^{***}$ $0.00007)$ $0.00005$ $0.00006^{***}$ $0.00012)$ $0.00003)$ $(0.00003)$ Soli ferility $0.128^+$ $0.012^ 0.0017^+$ $0.00033$ $(0.0003)$ Soli ferility $0.128^+$ $0.012^ 0.0007^+$ $0.00033$ $(0.0003)$ Soli ferility $0.128^+$ $0.012^ 0.0017^+$ $0.085^{**}$ $0.078^+$ $0.00012)$ $0.00033$ $(0.0003)$ Solpe of field $0.017^ 0.085^{**}$ $0.078^+$ $0.018^+$ $0.078^+$ $0.0007^ 0.0023^+$ $0.008^ 0.0007^ 0.0023^+$ $0.0083^ 0.0008^+$ $0.017^ 0.023^+$ $0.0008^+$ $0.017^ 0.023^+$ $0.0109^ 0.0034^+$ $0.034^+$ $0.021^ 0.0035^+$ $0.078^+$ $0.017^ 0.085^+$ $0.078^+$ $0.017^ 0.085^+$ $0.078^+$		Order Probit	Probit	Probit
Household size $0.07^{+}$ $0.0068^{+}$ $0.0064^{+}$ Age $(0.016)$ $(0.0038)$ $(0.0039)$ Age $0.0064$ $-0.0015$ $(0.0039)$ Age <sup>2</sup> $(0.0001)$ $(0.0003)$ $(0.0001)$ Education $0.122$ $0.00001$ $(0.00003)$ Education $0.122$ $0.028$ $(0.018)^{**}$ TLU $0.00028$ $0.0018^{**}$ $0.0018^{**}$ Non-food expenditure $(0.0005)$ $(0.0005)$ $(0.0005)$ Non-food expenditure $(0.0017)$ $(0.0005)$ $(0.0003)$ Soil fertility $0.128^{**}$ $0.012^{**}$ $(0.0003)$ Soil fertility $0.128^{**}$ $0.012^{**}$ $(0.0003)^{**}$ Soil fertility $0.128^{**}$ $0.012^{**}$ $0.0003^{**}$ Soil fertility $0.124^{**}$ $0.034^{**}$ $0.039^{**}$ Soil fertility $0.017^{**}$ $0.0083^{**}$ $0.078^{**}$ Soli fertility $0.017^{**}$ $0.028^{**}$ $0.078^{**}$ <		(11)	(12)	(13)
Age(0.016)(0.0038)(0.0039)Age-0.064-0.0015-0.0015 $Age^2$ 0.000010.000010.00001Education0.1220.02490.028 $(0.001)$ (0.0003)0.00003)0.00003Education0.1220.02490.028TLU0.000280.0018"0.0011"*** $(0.009)$ 0.000630.00065**0.0011"***Farm size-0.008-0.0077***-0.0085*** $(0.0223)$ (0.003)0.00006**Non-food expenditure0.000170.000030.00006** $(0.0017)$ 0.00003(0.0003)0.00003Soil fertility0.128*0.0120.0135Fertilizer use0.244***0.0340.039* $(0.104)$ (0.027)(0.027)(0.027)Slope of field0.01770.085***0.078** $(0.107)$ (0.028)(0.030)(0.030)Access to safety nets0.102*0.009**0.1002** $(0.076)$ (0.020)(0.020)(0.021)Iquib0.876***0.089***0.104** $(0.165)$ (0.018)(0.017)Iquib0.876***0.089***0.104** $(0.165)$ (0.025)(0.025)(0.026)Labor sharing(0.165)(0.025)(0.021) $(0.165)$ (0.021)(0.021)(0.021)Iddir(0.165)(0.021)(0.021)Connection to local authorities(1.48**0.043** $(0.019)$	Household size	0.027*	0.0068*	0.0064
Age-0.064-0.0015-0.0015 $Age^2$ (0.0152)(0.0035)(0.0034) $Age^2$ (0.0007)(0.00001)(0.00003) $Choold (0,0001)$ (0.00003)(0.00003) $Choold (0,0001)$ (0.00003)(0.00003) $Choold (0,0001)$ (0.00003)(0.00003) $Choold (0,0001)$ (0.00003)(0.00003) $TLU$ (0.0009)(0.0006)(0.0006) $Choold (0,0001)$ (0.0001)(0.0003)(0.00029)Non-food expenditure(0.0011)(0.00003)(0.0003)Soil fertility(0.128)(0.012)(0.0003)Soil fertility(0.124)(0.019)(0.19)Fertilizer use(0.244)(0.034)(0.039)Colored (0,0011)(0.023)(0.021)Slope of field(0.107)(0.023)(0.021)Land tenure(0.010)(0.023)(0.035)Access to safety nets(0.192***(0.0097)(0.122***(0.090)(0.036)(0.035)(0.035)Access to credit(0.165)(0.020)(0.020)Access to credit(0.165)(0.025)(0.021***(1uib(0.165)(0.025)(0.021***(1uib(0.165)(0.025)(0.021***(1uib(0.165)(0.025)(0.025)(1dir(0.165)(0.025)(0.021***(1uib(0.165)(0.021***(0.014)**(1uib(0.165)(0.021***(0.021****(1uib(0.165)(0.021*		(0.016)	(0.0038)	(0.0039)
$Age^2$ (0.0152)         (0.0035)         (0.0034) $Age^2$ 0.00007         0.00001         0.000013           Education         0.122         0.0249         0.028           (0.0005)         (0.0178)         (0.0178)         (0.0178)           TLU         0.00028         0.0018**         0.0011***           (0.0009)         (0.0005)         (0.0005)         (0.0006)**           Farm size         0.0017         0.00005         0.0006***           (0.0223)         (0.003)         (0.0029)**           Non-food expenditure         0.0017         0.00005         0.00006**           (0.019)         (0.019)         (0.019)         (0.019)           Soli fertility         0.128*         0.012         (0.013)           Gondon17         0.085**         (0.07)         (0.021)           Fertilizer use         0.244***         0.034         0.039*           Gondo17         0.085*         0.078**         0.078**           Gondo17         0.085*         0.078**         0.078**           Gondo10         0.017         0.023         0.021**           Land tenure         -0.011         0.0083         0.008*	Age	-0.064	-0.0015	-0.0015
Age <sup>2</sup> $0.0007$ $0.0001$ $0.00013$ Education $(0.0001)$ $(0.0003)$ $(0.0003)$ Education $(0.085)$ $(0.0178)$ $(0.018)$ TLU $(0.009)$ $(0.0006)$ $(0.0011)^{**}$ $(0.009)$ $(0.0006)$ $(0.0006)$ $(0.0025)$ Farm size $-0.008$ $-0.077^{**}$ $-0.0085^{**}$ $(0.0223)$ $(0.0003)$ $(0.0003)$ $(0.0003)$ Non-food expenditure $(0.0017)$ $(0.0003)$ $(0.0003)$ Soil fertility $0.128^{*}$ $0.012$ $(0.0003)$ Soil fertility $0.128^{*}$ $0.012$ $(0.0003)$ Soil fertility $0.128^{*}$ $0.012^{*}$ $(0.019)^{*}$ Fertilizer use $0.244^{**}$ $0.034$ $0.037^{*}$ Gope of field $0.0177$ $0.085^{***}$ $0.077^{**}$ Gologo $0.034$ $0.038$ $0.008^{***}$ Access to stept nets $0.192^{**}$ $0.092^{***}$ $0.102^{***}$ Access to credit	0	(0.0152)	(0.0035)	(0.0034)
a(0.0001)(0.00003)(0.00003)Education0.1220.02490.028TLU0.0005(0.0178)(0.018)(0.0006)(0.0006)(0.0006)Farm size-0.008-0.077**-0.0085***(0.0223)(0.003)(0.0003)(0.0003)Non-food expenditure0.00017(0.0003)(0.00003)Soil fertility0.128*0.012(0.0003)Soil fertility0.128*0.012(0.0003)Soil fertility0.128*0.012(0.019)Fertilizer use0.244**0.034(0.039*)(0.074)(0.019)(0.021)(0.027)Slope of field0.01770.085***0.078**(0.106)(0.027)(0.027)(0.027)Land tenure-0.0110.00830.008(0.107)(0.028)(0.030)(0.035)Access to safety nets0.192**0.092***0.102***(0.090)(0.026)(0.020)(0.020)Access to credit0.158*0.00970.12(0.016)(0.018)(0.017)(0.026)Labor sharing0.95***0.322***0.039***(0.165)(0.025)(0.026)(0.026)Labor sharing0.0155(0.025)(0.026)Labor sharing0.015*(0.021)(0.041)Relatives-0.048**-0.09***-0.01**(0.0199)(0.021)(0.041)(0.019)Connection to local authorities0.14**(	Age <sup>2</sup>	0.00007	0.00001	0.000013
Education $0.122$ $0.024$ $0.028$ TLU $0.00028$ $0.0178$ $0.018$ farm size $0.00028$ $0.0017^*$ $0.0085^{***}$ $0.0023$ $0.0033$ $0.0029^*$ Non-food expenditure $0.00017$ $0.00005$ $0.00005^{****}$ $0.00012$ $0.00003$ $0.00003$ $0.00003$ Soil fertility $0.128^*$ $0.012$ $0.0135$ fertilizer use $0.244^{***}$ $0.033$ $0.021$ Slope of field $0.0177$ $0.085^{***}$ $0.074^*$ $0.1041$ $0.0233$ $0.021$ $0.019^*$ Land tenure $0.0117$ $0.085^*$ $0.078^*$ $0.1077$ $0.083$ $0.008$ $0.0300$ Access to safety nets $0.192^*$ $0.0027$ $0.0227$ Land tenure $0.0177$ $0.0288$ $0.0300$ Access to credit $0.1666^*$ $0.0207^*$ $0.0122^*$ $0.00661^*$ $0.0188^*$ $0.0077^*$ $0.0201^*$	C .	(0.0001)	(0.00003)	(0.00003)
TLU $(0.085)$ $(0.0178)$ $(0.018)$ TLU $0.00028$ $0.0018^{**}$ $0.0011^{***}$ $0.0009$ $(0.0006)$ $(0.0006)$ Farn size $-0.008$ $-0.077^{***}$ $-0.0085^{***}$ $0.0223$ $(0.003)$ $(0.0029)$ Non-food expenditure $0.00017$ $0.00003$ $(0.0003)$ Soil fertility $0.128^{**}$ $0.012$ $(0.0003)$ Soil fertility $0.128^{**}$ $0.012$ $(0.019)$ Fertilizer use $0.244^{***}$ $0.034$ $0.039^{*}$ $(0.104)$ $(0.023)$ $(0.021)$ Slope of field $0.0177$ $0.085^{***}$ $0.078^{***}$ $(0.106)$ $(0.027)$ $(0.027)$ $(0.027)$ $(0.027)$ Land tenure $(0.106)$ $(0.027)$ $(0.027)$ Land tenure $(0.106)$ $(0.027)$ $(0.027)$ $(0.028)$ $(0.036)$ Access to safety nets $(0.199)$ $(0.036)$ $(0.035)$ Access to credit $0.158^{**}$ $0.099^{***}$ $0.102^{***}$ $(0.076)$ $(0.020)$ $(0.020)$ $(0.020)$ Access to extension $(0.166)$ $(0.18)$ $(0.017)$ $(0.191)$ $(0.025)^{***}$ $0.322^{***}$ $0.309^{***}$ $(0.192)^{***}$ $0.023^{***}$ $0.309^{***}$ $(0.192)^{***}$ $0.025^{***}$ $0.322^{***}$ $0.309^{***}$ $(0.076)^{***}$ $0.025^{***}$ $0.322^{***}$ $0.309^{***}$ $(0.076)^{***}$ $0.025^{***}$ $0.0225^{***}$ $0.025^{***}$ $(0.078)^{***}$ <	Education	0.122	0.0249	0.028
TLU $0.00028$ $0.0018^{++}$ $0.0011^{+++}$ Barm size $0.0008$ $0.00066$ $(0.0006)$ Farm size $0.00223$ $(0.003)$ $(0.0023)$ Non-food expenditure $0.00017$ $0.00005$ $0.0006^{++}$ $(0.00012)$ $(0.00003)$ $(0.00003)$ Soil fertility $0.128^{+}$ $0.012^{-}$ $(0.00003)^{+}$ Soil fertility $0.128^{+}$ $0.012^{-}$ $(0.00003)^{+}$ Soil fertility $0.074^{+}$ $0.034^{-}$ $0.039^{+}$ Gold fertility $0.074^{+}$ $0.034^{-}$ $0.039^{+}$ Solpe of field $0.0177^{-}$ $0.088^{++}$ $0.078^{+++}$ $(0.106)$ $(0.027)^{-}$ $(0.027)^{-}$ $(0.027)^{-}$ Land tenure $-0.011$ $0.0083^{-}$ $(0.036)^{-}$ Access to credit $0.192^{++}$ $0.092^{++}$ $0.1002^{++}$ $(0.090)^{-}$ $(0.036)^{-}$ $(0.018)^{-}$ $(0.0198^{-})$ $(access to credit       0.188^{+} 0.009^{++} 0.104^{++} (0.076)^{-} (0.018)^{-} (0.017)^{-} (0.$		(0.085)	(0.0178)	(0.018)
Farm size $(0.0009)$ $(0.0006)$ $(0.0006)$ Farm size $-0.008$ $-0.077^{**}$ $-0.0085^{***}$ $(0.0223)$ $(0.0003)$ $(0.0006^{**})$ Non-food expenditure $0.00017$ $0.00003$ $(0.00003)$ Soil fertility $0.128^{*}$ $0.012$ $0.0135$ $(0.074)$ $(0.019)$ $(0.019)$ $(0.019)$ Fertilizer use $0.244^{***}$ $0.034$ $0.039^{*}$ $(0.04)$ $(0.023)$ $(0.021)$ $(0.027)$ Slope of field $0.0177$ $0.085^{***}$ $0.078^{***}$ $(0.106)$ $(0.027)$ $(0.027)$ $(0.027)$ Land tenure $-0.011$ $0.0083$ $0.008$ $(0.090)$ $(0.366)$ $(0.036)$ $(0.035)$ Access to safety nets $(0.990)^{***}$ $(0.022)$ $(0.020)^{***}$ $(0.090)$ $(0.026)$ $(0.020)^{***}$ $(0.020)^{***}$ $(0.076)$ $(0.020)$ $(0.020)^{***}$ $(0.017)^{***}$ $(0.076)$ $(0.020)$ $(0.020)^{***}$ $(0.021)^{***}$ $(0.076)$ $(0.025)$ $(0.025)^{***}$ $(0.025)^{***}$ $(0.076)$ $(0.025)^{****}$ $(0.322^{***})^{***}$ $(0.025)^{***}$ $(1uib$ $(0.165)$ $(0.025)^{***}$ $(0.025)^{***}$ $(1uib$ $(0.23^{***})^{***}$ $(0.025)^{***}$ $(0.025)^{***}$ $(1uib$ $(0.23^{***})^{***}$ $(0.025)^{****}$ $(0.025)^{***}$ $(1uib$ $(0.23^{***})^{***}$ $(0.025)^{****}$ $(0.025)^{****}$ $(1uib$ $(0.23^{***})^{***}$ <	TLU	0.00028	0.0018**	0.0011***
Farm size $-0.008^{+}$ $-0.077^{+is}$ $-0.0085^{+ss}$ Non-food expenditure $0.00017$ $0.0003$ $(0.0029)^{-}$ Non-food expenditure $0.00017$ $0.00003$ $(0.00003)^{-}$ Soil fertility $0.128^{+}$ $0.012$ $0.00003^{+}$ Soil fertility $0.128^{+}$ $0.012$ $0.00003^{+}$ Soil fertility $0.0744^{+}$ $0.034^{+}$ $0.039^{+}$ Good (0.0023) $(0.021)^{+}$ $0.021^{+}$ $0.021^{+}$ Slope of field $0.0177^{-}$ $0.085^{+}$ $0.077^{-}$ Land tenure $-0.011^{-}$ $0.0883^{+}$ $0.078^{+}$ Access to safety nets $0.192^{+s}$ $0.0023^{+}$ $0.002^{+}$ Correst to credit $0.076^{+}$ $0.020^{+}$ $0.002^{+}$ Access to credit $0.076^{+}$ $0.020^{+}$ $0.012^{+}$ Iquib $0.87^{+*}$ $0.322^{+*}$ $0.309^{+*}$ Iquib $0.87^{+*}$ $0.025^{+}$ $0.022^{+}$ Iquib $0.87^{+*}$ $0.025^{+}$ $0.022^{+}$ Iquib $0.87^{+*}$ $0.025^{+}$		(0.0009)	(0.0006)	(0.0006)
Non-food expenditure $(0.0223)$ $(0.003)$ $(0.0005)^*$ Non-food expenditure $0.00017$ $0.00005$ $0.00006^{**}$ $(0.0012)$ $(0.0003)$ $(0.0003)$ Sol fertility $0.128^*$ $0.012$ $0.0135$ Fertilizer use $0.244^{**}$ $0.034$ $0.039^*$ $(0.104)$ $(0.023)$ $(0.021)$ Slope of field $0.0177$ $0.088^{**}$ $0.078^*$ $(0.106)$ $(0.027)$ $(0.027)$ Land tenure $-0.011$ $0.0083$ $0.008$ $(0.107)$ $(0.028)$ $(0.030)$ Access to safety nets $0.192^*$ $0.0097^*$ $(0.090)$ $(0.366)$ $(0.035)$ Access to credit $0.18^*$ $0.0097$ $(0.076)$ $(0.020)$ $(0.020)$ Access to extension $0.104$ $0.024$ $(0.19)$ $(0.025)$ $(0.026)$ Iquib $0.876^**$ $0.322^**$ $(0.125)$ $(0.0415)$ $(0.025)$ Iddir $-0.239^*$ $-0.114^{**}$ $(0.125)$ $(0.0415)$ Iddir $0.0199$ $(0.008)$ $(0.019)$ $(0.0017)$ $(0.019)$ $(0.021)$ Connection to local authorities $0.148^*$ $(0.011)^*$ $(0.041)$ $(0.023)$ $(0.021)$ Connection to local authorities $0.148^*$ $(0.019)^*$ $(0.021)$ Connection to local authorities $0.148^*$ $(0.023)$ $(0.001)$ $(0.023)$ $(0.001)$ $(0.023)$ $(0.021)$ <td>Farm size</td> <td>-0.008</td> <td>-0.077***</td> <td>-0.0085<sup>***</sup></td>	Farm size	-0.008	-0.077***	-0.0085 <sup>***</sup>
Non-food expenditure $0.00017$ $0.00005$ $0.00006^{**}$ Soil fertility $(0.00012)$ $(0.00003)$ $(0.00003)$ Soil fertility $(0.128^{*})$ $(0.019)$ $(0.019)$ Fertilizer use $0.244^{***}$ $0.034$ $0.039^{*}$ Slope of field $0.0177$ $0.085^{***}$ $0.078^{**}$ Land tenure $-0.011$ $0.0083$ $0.008$ Access to safety nets $0.192^{**}$ $0.092^{***}$ $0.1002^{***}$ Access to credit $0.177$ $0.0283$ $0.030$ Access to credit $0.192^{**}$ $0.092^{***}$ $0.1002^{***}$ $(0.090)$ $0.0366$ $(0.017)$ $0.0220$ $0.020^{***}$ Access to credit $0.166$ $0.018$ $0.017$ $0.020^{***}$ Iquib $0.876^{***}$ $0.089^{***}$ $0.104^{***}$ $(0.125)$ $(0.025)$ $(0.026)^{****}$ $0.025^{****}$ Iquib $0.876^{***}$ $0.322^{***}$ $0.339^{****}$ Iquib $0.065^{***}$		(0.0223)	(0.003)	(0.0029)
Soil fertility $(0.00012)$ $(0.0003)$ $(0.0003)$ Soil fertility $0.128^{+}$ $0.012$ $0.0135$ $(0.074)$ $(0.019)$ $(0.019)$ Fertilizer use $0.244^{+**}$ $0.034$ $0.039^{+}$ $(0.104)$ $(0.023)$ $(0.021)$ Slope of field $0.0177$ $0.085^{+**}$ $0.078^{+***}$ $(0.106)$ $(0.027)$ $(0.027)$ $(0.027)$ Land tenure $-0.011$ $0.0083$ $0.008$ $(0.107)$ $(0.028)$ $(0.030)^{-*}$ Access to safety nets $(0.192^{-*})$ $(0.002^{-**})$ $(0.090)$ $(0.366)$ $(0.035)$ Access to credit $0.158^{+*}$ $0.0097$ $0.012$ $(0.076)$ $(0.024)$ $(0.108)$ $(0.017)$ Iquib $0.876^{+**}$ $0.089^{+**}$ $0.104^{+**}$ $(0.191)$ $(0.025)$ $(0.026)$ $(0.26)$ Labor sharing $0.95^{+**}$ $0.322^{+**}$ $0.309^{+**}$ $(0.125)$ $(0.014^{+**})$ $(0.025)$ $(0.025)^{-}$ Iddir $-0.239^{*}$ $-0.11^{+**}$ $-0.11^{+**}$ $(0.165)$ $(0.0212)$ $(0.023)$ $(0.041)$ Relatives $-0.048^{**}$ $-0.09^{***}$ $0.044^{**}$ $(0.019)$ $(0.021)$ $(0.021)$ $(0.021)^{-}$ Connection to local authorities $0.148^{+**}$ $0.004^{+**}$ $(0.019)^{-}$ Early adopters $0.019^{+**}$ $(0.021)^{-}$ $(0.021)^{-}$ $(0.023)$ $(0.001)^{-}$ $(0.021)^{-}$ $(0.021)^{-}$ </td <td>Non-food expenditure</td> <td>0.00017</td> <td>0.00005</td> <td>0.00006<sup>***</sup></td>	Non-food expenditure	0.00017	0.00005	0.00006 <sup>***</sup>
Soil fertility $0.128^*$ $0.012$ $0.0135^*$ Fertilizer use $0.24^{4**}$ $0.034$ $0.039^*$ Slope of field $0.0177$ $0.085^{5**}$ $0.021$ Slope of field $0.0177$ $0.085^{5**}$ $0.078^{**}$ Land tenure $-0.011$ $0.0083$ $0.008$ Access to safety nets $0.192^{**}$ $0.092^{**}$ $0.0023^*$ $0.090$ $0.0356$ $0.035^*$ Access to credit $0.192^{**}$ $0.092^{**}$ $0.0024^*$ $0.090$ $0.0356$ $0.035^*$ Access to credit $0.158^{**}$ $0.0097$ $0.012$ $(0.076)$ $(0.020)$ $(0.020)$ $(0.020)$ Access to extension $0.104$ $0.024$ $0.0198$ $(0.119)$ $(0.025)$ $(0.026)$ $(0.026)$ Labor sharing $0.95^{***}$ $0.322^{***}$ $0.309^{***}$ $(0.119)$ $(0.025)$ $(0.041)$ $(0.041)$ Relatives $-0.048^{**}$ $-0.009^{***}$ $0.014^{**}$ $(0.019)$ $(0.021)$ $(0.041)$	I	(0.00012)	(0.00003)	(0.00003)
$I_{exc}$ $(0.074)$ $(0.019)$ $(0.019)$ Fertilizer use $0.244^{***}$ $0.034$ $0.039^{\circ}$ Slope of field $0.0177$ $0.085^{***}$ $0.078^{***}$ Land tenure $-0.011$ $0.0083$ $0.008$ $(0.107)$ $(0.028)$ $(0.030)$ Access to safety nets $0.192^{**}$ $0.092^{***}$ $(0.107)$ $(0.028)$ $(0.030)$ Access to credit $0.192^{**}$ $0.092^{***}$ $(0.090)$ $(0.36)$ $(0.035)$ Access to credit $0.158^{**}$ $0.0097$ $(0.17)$ $(0.020)$ $(0.020)$ Access to extension $0.104$ $0.024$ $(0.066)$ $(0.018)$ $(0.017)$ Iquib $0.876^{**}$ $0.188^{**}$ $(0.119)$ $(0.025)$ $(0.026)$ Labor sharing $0.95^{***}$ $0.322^{***}$ $(0.125)$ $(0.0415)$ $(0.041)$ Relatives $-0.048^{**}$ $-0.114^{***}$ $(0.125)$ $(0.0415)$ $(0.041)$ Relatives $0.0165$ $0.0212$ $(0.023)$ $(0.008)$ $(0.0045)$ Trust $0.0165$ $0.0211$ $(0.023)$ $(0.004)$ $(0.004)$ $(0.023)$ $(0.004)$ $(0.004)$ $(0.024)$ $0.004^{***}$ $0.004^{***}$ $(0.025)$ $(0.025)$ $(0.025)$ Iddir $-0.239^{*}$ $-0.114^{***}$ $(0.119)$ $(0.021)$ $(0.021)$ $(0.021)$ $(0.021)$ $(0.021)$ $(0.022)$ $(0.021)$	Soil fertility	0.128*	0.012	0.0135
Fertilizer use $0.244^{***}$ $0.034^{*}$ $0.039^{*'}$ Slope of field $0.0177$ $0.085^{***}$ $0.078^{**}$ $0.106$ $0.0277$ $0.00277$ Land tenure $-0.011$ $0.0083$ $0.008$ $0.192^{**}$ $0.092^{***}$ $0.1002^{***}$ $0.090$ $0.0366$ $(0.035)$ Access to safety nets $0.192^{**}$ $0.092^{***}$ $0.1002^{***}$ $0.090$ $0.0366$ $(0.035)$ $0.022^{***}$ $0.076$ $0.020$ $(0.020)$ $0.020$ Access to credit $0.158^{**}$ $0.0097$ $0.012$ $(0.076)$ $(0.020)$ $(0.020)$ $0.020$ Access to extension $0.104$ $0.024$ $0.0198$ $(0.017)$ $(0.025)$ $(0.025)$ $(0.026)$ Labor sharing $0.95^{***}$ $0.322^{***}$ $0.309^{***}$ $(0.15)$ $(0.025)$ $(0.025)$ $(0.025)$ Idir $-0.048^{**}$ $-0.019^{***}$ $-0.01^{***}$ $(0.155)$ $(0.021)$ $(0.021)$ $(0.021)$ <		(0.074)	(0.019)	(0.019)
	Fertilizer use	$0.244^{***}$	0.034	0.039*
Slope of field $0.017^{2}$ $0.085^{***}$ $0.078^{***}$ Land tenure $(0.106)$ $(0.027)$ $(0.027)$ Land tenure $-0.011$ $0.0083$ $0.008$ Access to safety nets $0.192^{**}$ $0.092^{***}$ $0.1002^{***}$ Access to credit $0.192^{**}$ $0.0997$ $0.102^{***}$ Access to credit $0.076^{*}$ $0.0020$ $(0.020)$ Access to extension $0.104$ $0.024$ $0.0198$ $(0.066)$ $(0.018)$ $(0.017)$ $(0.020)$ Iquib $0.876^{***}$ $0.322^{***}$ $0.309^{***}$ $(0.165)$ $(0.025)$ $(0.026)$ $(0.026)$ Labor sharing $0.95^{***}$ $0.322^{***}$ $0.309^{***}$ $(0.165)$ $(0.025)$ $(0.025)$ $(0.025)$ Iddir $-0.048^{**}$ $-0.09^{***}$ $-0.11^{****}$ $(0.119)$ $(0.021)$ $(0.021)$ $(0.021)$ Connection to local authorities $0.148^{**}$ $0.0415$ $(0.0415)$ $(0.071)$ $(0.0021)$ $(0.0021)$ $(0.021)$ <		(0.104)	(0.023)	(0.021)
arr protection(0.106)(0.027)(0.027)Land tenure-0.0110.00830.008 $(0.107)$ (0.028)(0.030)Access to safety nets0.192**0.092** $(0.090)$ (0.036)(0.035)Access to credit0.158**0.0097 $(0.076)$ (0.020)(0.020)Access to extension0.1040.024 $(0.066)$ (0.018)(0.017)Iquib0.876**0.089** $(0.165)$ (0.025)(0.026)Labor sharing0.95***0.322** $(0.165)$ (0.025)(0.025)Iddir-0.239*-0.114*** $(0.125)$ (0.041)Relatives-0.048**-0.09*** $(0.199)$ (0.008)(0.041)Trust0.01650.0212 $(0.089)$ (0.21)(0.021)Connection to local authorities0.148*0.041* $(0.021)$ (0.023)(0.001)Connection to local authorities0.19**0.004** $(0.023)$ (0.001)(0.0004)Climate shock-0.08*-0.021 $(0.0798)$ (0.0055)(0.016)Prob> chi20.00000.0000Prob> chi20.2530.5280.530.5280.53Log likelihood-1092.6-363.5Number of observation11411141	Slope of field	0.0177	0.085***	0.078***
Land tenure $-0.011$ $0.0083$ $0.008$ Access to safety nets $0.192^{**}$ $0.0228$ $(0.030)$ Access to credit $0.192^{**}$ $0.092^{***}$ $0.1002^{***}$ Access to credit $0.158^{**}$ $0.0097$ $0.012$ Access to extension $0.164$ $0.024$ $0.0198$ $0.056$ $(0.020)$ $(0.020)$ $(0.020)$ Access to extension $0.104$ $0.024$ $0.0198$ $0.014$ $0.024$ $0.0198$ $(0.017)$ Iquib $0.876^{**}$ $0.392^{***}$ $0.309^{***}$ $0.192$ $(0.19)$ $(0.025)$ $(0.026)$ Labor sharing $0.95^{***}$ $0.322^{***}$ $0.309^{***}$ $(0.165)$ $(0.025)$ $(0.025)$ $(0.025)$ Iddir $-0.239^{*}$ $-0.114^{***}$ $-0.119^{***}$ $(0.125)$ $(0.0415)$ $(0.041)$ $(0.041)$ Relatives $-0.048^{**}$ $-0.009^{***}$ $-0.01^{***}$ $(0.0199)$ $(0.008)$ $(0.0045)$ $(0.0045)$ Trust $(0.019)$ $(0.021)$ $(0.021)$ Connection to local authorities $0.148^{**}$ $0.043^{**}$ $0.004^{***}$ $(0.0023)$ $(0.001)$ $(0.0004)$ $(0.004)^{***}$ Climate shock $-0.084$ $-0.021$ $-0.024$ $(0.0798)$ $(0.0055)$ $(0.016)$ Prob> chi2 $0.0000$ $0.0000$ $0.0000$ Pseudo R2 $0.253$ $0.528$ $0.53$ Log likelihood $-1092.6$ $-363.5$ $-302.9$ </td <td></td> <td>(0.106)</td> <td>(0.027)</td> <td>(0.027)</td>		(0.106)	(0.027)	(0.027)
Access to safety nets $(0.107)$ $(0.028)$ $(0.030)$ Access to credit $0.192^{**}$ $0.092^{***}$ $0.1002^{***}$ Access to credit $0.158^{**}$ $0.0097$ $0.012$ $(0.076)$ $(0.020)$ $(0.020)$ Access to extension $0.104$ $0.024$ $0.0198$ $(0.066)$ $(0.018)$ $(0.017)$ Iquib $0.876^{***}$ $0.089^{***}$ $0.104^{***}$ $(0.19)$ $(0.255)$ $(0.026)$ Labor sharing $0.95^{***}$ $0.322^{***}$ $0.309^{***}$ $(0.165)$ $(0.025)$ $(0.025)$ Iddir $-0.239^{*}$ $-0.114^{***}$ $-0.119^{***}$ $(0.125)$ $(0.0415)$ $(0.041)$ Relatives $-0.048^{**}$ $-0.009^{***}$ $-0.01^{**}$ $(0.0199)$ $(0.008)$ $(0.0045)$ Trust $0.0165$ $0.0212$ $0.023$ $(0.071)$ $(0.044^{**})$ $(0.019)$ Early adopters $0.019^{**}$ $0.004^{***}$ $(0.0023)$ $(0.001)$ $(0.0004)$ Climate shock $-0.084$ $-0.021$ $-0.024$ $(0.0798)$ $(0.0055)$ $(0.016)$ Prob> chi2 $0.0000$ $0.0000$ $0.0000$ Prob> chi2 $0.0000$ $0.0000$ $0.0000$ Prob> chi2 $0.253$ $0.528$ $0.53$ Log likelihood $-1092.6$ $-363.5$ $-302.9$	Land tenure	-0.011	0.0083	0.008
Access to safety nets $0.192^{**}$ $0.092^{**}$ $0.1002^{***}$ Access to credit $0.158^{**}$ $0.0097$ $0.012$ Access to credit $0.158^{**}$ $0.0097$ $0.012$ Access to extension $0.104$ $0.020$ $(0.020)$ Access to extension $0.104$ $0.024$ $0.0198$ $(0.066)$ $(0.018)$ $(0.017)$ Iquib $0.876^{**}$ $0.089^{***}$ $0.104^{***}$ $(0.119)$ $(0.025)$ $(0.025)$ Labor sharing $0.95^{***}$ $0.322^{***}$ $0.309^{***}$ $(0.165)$ $(0.025)$ $(0.025)$ Iddir $-0.239^{*}$ $-0.114^{***}$ $-0.119^{***}$ $(0.125)$ $(0.0415)$ $(0.041)$ Relatives $-0.048^{**}$ $-0.009^{***}$ $-0.01^{**}$ $(0.0199)$ $(0.008)$ $(0.0045)$ Trust $0.0165$ $0.0212$ $0.023$ $(0.071)$ $(0.041^{***})$ $0.004^{***}$ $(0.071)$ $(0.041^{***})$ $0.044^{***}$ $(0.071)$ $(0.041^{***})$ $0.044^{***}$ $(0.071)$ $(0.041^{***})$ $0.044^{***}$ $(0.071)$ $(0.041^{***})$ $0.004^{***}$ $(0.071)$ $(0.041^{***})$ $0.004^{***}$ $(0.071)$ $(0.041^{***})$ $0.004^{***}$ $(0.071)$ $(0.041^{***})$ $0.004^{***}$ $(0.071)$ $(0.041^{***})$ $0.004^{***}$ $(0.071)$ $(0.041^{***})$ $0.004^{***}$ $(0.071)$ $(0.041^{***})$ $0.004^{***}$ $(0.071)$ <		(0.107)	(0.028)	(0.030)
Access to credit $(0.090)$ $(0.036)$ $(0.035)$ Access to credit $0.158^{**}$ $0.0097$ $0.012$ $(0.076)$ $(0.020)$ $(0.020)$ Access to extension $0.104$ $0.024$ $0.0198$ $(0.066)$ $(0.018)$ $(0.017)$ Iquib $0.876^{***}$ $0.089^{***}$ $0.104^{***}$ $(0.119)$ $(0.025)$ $(0.026)$ Labor sharing $0.95^{***}$ $0.322^{***}$ $0.309^{***}$ $(0.125)$ $(0.025)$ $(0.025)$ $(0.025)$ Iddir $-0.239^{**}$ $0.114^{***}$ $-0.119^{***}$ $(0.125)$ $(0.0415)$ $(0.041)$ Relatives $-0.04^{**}$ $-0.09^{***}$ $(0.199)$ $(0.008)$ $(0.0045)$ Trust $0.0165$ $0.0212$ $0.023$ Connection to local authorities $0.148^{**}$ $0.044^{**}$ $(0.071)$ $(0.044)$ $(0.019)$ Early adopters $0.019^{***}$ $0.004^{***}$ $(0.0023)$ $(0.001)$ $(0.004)$ Climate shock $-0.084$ $-0.021$ $(0.0798)$ $(0.0055)$ $(0.016)$ Prob> chi2 $0.0000$ $0.0000$ $0.0000$ Pseudo R2 $0.253$ $0.528$ $0.53$ Log likelihood $-1092.6$ $-363.5$ $-302.9$ Number of observation $1141$ $1141$ $1141$	Access to safety nets	0.192**	0.092***	0.1002***
Access to credit $0.158^{**}$ $0.0097$ $0.012$ Access to extension $0.104$ $0.024$ $0.0198$ $(0.066)$ $(0.018)$ $(0.017)$ Iquib $0.876^{***}$ $0.089^{***}$ $0.104^{****}$ $(0.119)$ $(0.025)$ $(0.026)$ Labor sharing $0.95^{***}$ $0.322^{***}$ $0.309^{***}$ $(0.165)$ $(0.025)$ $(0.025)$ Iddir $-0.239^{*}$ $-0.114^{***}$ $-0.119^{***}$ $(0.125)$ $(0.0415)$ $(0.041)$ Relatives $-0.048^{**}$ $-0.009^{***}$ $-0.01^{**}$ $(0.125)$ $(0.0415)$ $(0.041)$ Relatives $-0.048^{**}$ $-0.009^{***}$ $-0.01^{**}$ $(0.125)$ $(0.0415)$ $(0.041)$ Relatives $-0.048^{**}$ $-0.009^{***}$ $-0.01^{**}$ $(0.0199)$ $(0.008)$ $(0.0045)$ $(0.0045)$ Trust $0.0165$ $0.0212$ $0.023$ $(0.071)$ $(0.021)$ $(0.021)$ Connection to local authorities $0.148^{**}$ $0.004^{***}$ $(0.071)$ $(0.0044)$ $(0.019)$ Early adopters $0.019^{***}$ $0.004^{***}$ $(0.095)$ $(0.022)$ $(0.021)$ Risk aversion $0.57^{***}$ $0.042^{***}$ $0.139^{***}$ $(0.0798)$ $(0.0055)$ $(0.016)$ Prob> chi2 $0.0000$ $0.0000$ $0.0000$ Pseudo R2 $0.253$ $0.528$ $0.53$ Log likelihood $-1092.6$ $-363.5$ $-302.9$ Number		(0.090)	(0.036)	(0.035)
Intervent $(0.076)$ $(0.021)$ $(0.022)$ Access to extension $0.104$ $0.024$ $0.0198$ $(0.066)$ $(0.018)$ $(0.017)$ Iquib $0.876^{***}$ $0.089^{***}$ $0.104^{****}$ $(0.19)$ $(0.025)$ $(0.026)$ Labor sharing $0.95^{***}$ $0.322^{***}$ $0.309^{***}$ $(0.165)$ $(0.025)$ $(0.025)$ Iddir $-0.239^{*}$ $-0.114^{***}$ $-0.119^{***}$ $(0.125)$ $(0.0415)$ $(0.041)$ Relatives $-0.048^{**}$ $-0.09^{***}$ $-0.01^{**}$ $(0.0199)$ $(0.008)$ $(0.0045)$ Trust $0.0165$ $0.0211$ $(0.021)$ Connection to local authorities $0.148^{**}$ $0.044^{**}$ $(0.071)$ $(0.044)$ $(0.019)$ Early adopters $0.019^{***}$ $0.004^{***}$ $(0.0023)$ $(0.001)$ $(0.004)$ Climate shock $0.07^{***}$ $0.042^{***}$ $(0.0798)$ $(0.0055)$ $(0.016)$ Prob> chi2 $0.020$ $0.0000$ $0.0000$ Prob> chi2 $0.253$ $0.528$ $0.53$ Log likelihood $-1092.6$ $-363.5$ $-302.9$ Number of observation $1141$ $1141$ $1141$	Access to credit	0.158**	0.0097	0.012
Access to extension $(0.104)$ $(0.024)$ $(0.0198)$ Iquib $(0.066)$ $(0.018)$ $(0.017)$ Iquib $0.876^{***}$ $0.089^{***}$ $0.104^{***}$ $(0.119)$ $(0.025)$ $(0.026)$ Labor sharing $0.95^{***}$ $0.322^{***}$ $0.309^{***}$ $(0.165)$ $(0.025)$ $(0.025)$ Iddir $-0.239^{*}$ $-0.114^{***}$ $-0.119^{***}$ $(0.125)$ $(0.0415)$ $(0.041)$ Relatives $-0.048^{**}$ $-0.009^{***}$ $-0.01^{**}$ $(0.0199)$ $(0.008)$ $(0.0045)$ Trust $0.0165$ $0.0212$ $0.023$ $(0.089)$ $(0.021)$ $(0.021)$ Connection to local authorities $0.148^{**}$ $0.043^{**}$ $(0.071)$ $(0.044)$ $(0.019)$ Early adopters $(0.019^{***})$ $0.004^{***}$ $(0.0023)$ $(0.001)$ $(0.0004)$ Climate shock $-0.084$ $-0.021$ $(0.0798)$ $(0.0055)$ $(0.016)$ Prob> chi2 $0.0000$ $0.0000$ $0.0000$ Pseudo R2 $0.253$ $0.528$ $0.53$ Log likelihood $-1092.6$ $-363.5$ $-302.9$		(0.076)	(0.020)	(0.020)
Intervention $(0.066)$ $(0.018)$ $(0.017)$ Iquib $0.876^{***}$ $0.089^{***}$ $0.104^{***}$ $(0.119)$ $(0.025)$ $(0.026)$ Labor sharing $0.95^{***}$ $0.322^{***}$ $0.309^{***}$ $(0.165)$ $(0.025)$ $(0.025)$ Iddir $-0.239^{*}$ $-0.114^{***}$ $-0.119^{***}$ $(0.125)$ $(0.0415)$ $(0.041)$ Relatives $-0.048^{**}$ $-0.009^{***}$ $-0.11^{**}$ $(0.199)$ $(0.008)$ $(0.0045)$ Trust $0.0165$ $0.0212$ $0.023$ $(0.071)$ $(0.021)$ $(0.021)$ Connection to local authorities $0.148^{**}$ $0.043^{**}$ $(0.071)$ $(0.021)$ $(0.019)$ Early adopters $0.019^{***}$ $0.004^{***}$ $(0.0023)$ $(0.001)$ $(0.0004)$ Climate shock $-0.084$ $-0.021$ $(0.0798)$ $(0.0055)$ $(0.016)$ Prob> chi2 $0.0000$ $0.0000$ $0.0000$ Pseudo R2 $0.253$ $0.528$ $0.53$ Log likelihood $-1092.6$ $-363.5$ $-302.9$ Number of observation $1141$ $1141$ $1141$	Access to extension	0.104	0.024	0.0198
Iquib $(0.076^{***})$ $(0.089^{***})$ $(0.104^{***})$ Labor sharing $0.976^{***}$ $0.089^{***}$ $0.302^{***}$ $(0.119)$ $(0.025)$ $(0.026)$ Iddir $-0.239^{*}$ $-0.114^{***}$ $-0.119^{***}$ $(0.165)$ $(0.025)$ $(0.025)$ Iddir $-0.239^{*}$ $-0.114^{***}$ $-0.119^{***}$ $(0.125)$ $(0.0415)$ $(0.041)$ Relatives $-0.048^{**}$ $-0.009^{***}$ $-0.01^{**}$ $(0.0199)$ $(0.008)$ $(0.0045)$ Trust $0.0165$ $0.0212$ $0.023$ Connection to local authorities $0.148^{**}$ $0.043^{**}$ $0.044^{**}$ $(0.071)$ $(0.044)$ $(0.019)$ Early adopters $0.019^{***}$ $0.004^{***}$ $0.004^{***}$ $(0.095)$ $(0.021)$ $(0.024)$ Climate shock $-0.084$ $-0.021$ $-0.024$ $(0.0798)$ $(0.0055)$ $(0.016)$ Prob> chi2 $0.0000$ $0.0000$ $0.0000$ Pseudo R2 $0.253$ $0.528$ $0.53$ Log likelihood $-1092.6$ $-363.5$ $-302.9$ Number of observation $1141$ $1141$ $1141$		(0.066)	(0.018)	(0.017)
NameOne of the second sec	Iauib	0.876***	0.089***	0.104***
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Larry despension $0.001$ $0.001$ $0.001$ (0.0023)(0.001)(0.004)Climate shock $-0.084$ $-0.021$ $0.095$ (0.022)(0.021)Risk aversion $0.57^{***}$ $0.042^{***}$ $0.57^{***}$ $0.042^{***}$ $0.139^{***}$ $(0.0798)$ (0.0055)(0.016)Prob> chi2 $0.253$ $0.528$ $0.53$ Log likelihood $-1092.6$ $-363.5$ $-302.9$ Number of observation $1141$ $1141$ $1141$	Early adopters	$0.019^{***}$	$0.004^{***}$	0.004***
Climate shock $-0.084$ $-0.021$ $-0.024$ (0.095)(0.022)(0.021)Risk aversion $0.57^{***}$ $0.042^{***}$ $0.139^{***}$ (0.0798)(0.0055)(0.016)Prob> chi2 $0.253$ $0.528$ $0.53$ Log likelihood $-1092.6$ $-363.5$ $-302.9$ Number of observation $1141$ $1141$ $1141$		(0.0023)	(0,001)	(0,0004)
Ninke bioon $0.001$ $0.001$ $0.001$ Risk aversion $(0.095)$ $(0.022)$ $(0.021)$ $0.57^{***}$ $0.042^{***}$ $0.139^{***}$ $(0.0798)$ $(0.0055)$ $(0.016)$ $Prob> chi2$ $0.0000$ $0.0000$ $Pseudo R2$ $0.253$ $0.528$ $0.53$ Log likelihood $-1092.6$ $-363.5$ $-302.9$ Number of observation $1141$ $1141$ $1141$	Climate shock	-0.084	-0.021	-0.024
Risk aversion $(0.07)^{***}$ $(0.022^{***})^{**}$ $(0.021^{***})^{**}$ $0.57^{***}$ $0.042^{***}$ $0.139^{***}$ $(0.0798)$ $(0.0055)$ $(0.016)$ $Prob> chi2$ $0.0000$ $0.0000$ $Pseudo R2$ $0.253$ $0.528$ $0.53$ Log likelihood $-1092.6$ $-363.5$ $-302.9$ Number of observation $1141$ $1141$ $1141$		(0.095)	(0.021)	(0.021)
Number of observation $0.0798$ $0.0012$ $0.139$ $(0.0798)$ $(0.0055)$ $(0.016)$ $Prob> chi2$ $0.0000$ $0.0000$ $Pseudo R2$ $0.253$ $0.528$ $0.53$ Log likelihood $-1092.6$ $-363.5$ $-302.9$ Number of observation $1141$ $1141$ $1141$	Risk aversion	(0.093)	(0.022) 0.042***	0.139***
Prob> chi2       0.0000       0.0000       0.0000         Pseudo R2       0.253       0.528       0.53         Log likelihood       -1092.6       -363.5       -302.9         Number of observation       1141       1141       1141		(0.0798)	(0.0055)	(0.016)
Pseudo R2     0.253     0.528     0.53       Log likelihood     -1092.6     -363.5     -302.9       Number of observation     1141     1141	Prob> chi?	0.0000	0.0000	0.0000
Log likelihood         -1092.6         -363.5         -302.9           Number of observation         1141         1141         1141	Pseudo R2	0.253	0.528	0.53
Number of observation         1141         1141         1141	Log likelihood	-1092.6	-363 5	-302.9
	Number of observation	1141	1141	1141

Table 4.10: Order Probit and Probit models for robustness check

<sup>\*</sup>indicates statistical significance at the 10% level, <sup>\*\*</sup> significant at the 5% level, <sup>\*\*\*</sup> significant at the 1% level. Model 12 reports results using the 5-point measure of risk aversion while model 13 reports results using the two categories of risk aversion. Our final robustness check is with regard to the coding of the risk-aversion variable. While estimating the effects of risk-aversion, we can use either the five-point measure of risk-aversion directly or simply examine two categories of risk-aversion (risk-averse versus risk-neutral to loving). As a robustness check, we estimated our model using two categories and the five points directly as a measure of risk-aversion. Our result remains consistent and the effect of risk-aversion remains the same while using the five point measures of risk-aversion directly and two categories (risk-averse versus risk-loving households).

#### 4.8 Conclusion and implications

This paper presented an analysis of the effects of social capital on smallholder adoption of improved land management strategies. Specifically, the study has examined the differential effects of social capital on technology adoption across households with heterogonous levels of risk-aversion and formal credit accesses. At a methodological level, the paper used data from 2004 and 2009 rounds of the Ethiopian Household Survey (ERHS) to estimate different panel and cross-section model specifications explaining the adoption of innovative land management practices. In particular, we estimated a random effect probit and fixed effect logit model of adoption to examine the effects of social capital. Since most of the social capital indicators change only rarely over time, we presented a pseudo-fixed effect model of adoption following Mundlak (1978). Finally we presented IV-estimation results by instrumenting the social capital variables to control for potential endogeneity problems.

Our result shows that social capital is a significant determinant of adoption of improved land management practices. In particular, the various aspects of social capital affect adoption differently. For example, membership in labour sharing arrangements, membership in informal local saving and credit association and connection to local authorities were found to have a positive and significant effect on the probability of adopting improved land management practices. However, other forms of social capital, in our model having large number of relatives and membership in funeral insurance arrangements, were found to affect adoption negatively.

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Adoption of technologies such as improved land management practices requires formal financial access. In the absence of reliable formal credit markets, farmers may even become reluctant to adopt technologies that enhance productivity while reducing exposure to risk due to supply side constraints. In this regard our results further paint an interesting picture by revealing that some forms of social capital can at least be partial substitutes for formal credit markets. This implies that when modern sources of credit are missing, traditional community networks may serve as a source of finance. As such, policy interventions should consider promoting formal credit access as well as scaling up the capacity of informal social networks through provision of initial resources. Finally our finding underscores the importance of considering attitudes towards risk. Our results confirmed that the effect of social capital across households holding heterogeneous risk-aversion levels is different.

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## 4.10 Appendix

	Membership to	Connection to	Iquib	Iddir
	labor sharing	local authorities	-	
Household size	-0.0028	$0.0205^{***}$	$0.0118^{**}$	0.002
	(0.0065)	(0.0054)	(0.0054)	(0.003)
Age	-0.0006	0.0003	-0.00015	-0.0009
	(0.0009)	(0.0011)	(0.0008)	(0.0007)
Education	$0.098^{***}$	$0.139^{***}$	0.022	$0.061^{***}$
	(0.032)	(0.030)	(0.028)	(0.018)
TLU	0.0003	-0.0027	$0.0013^{***}$	0.0001
	(0.0003)	(0.0007)	(0.0003)	(0.0002)
Farm size	0.004	0.0076	-0.0048	-0.0069
	(0.006)	(0.0028)	(0.006)	(0.005)
Land tenure	-0.023	-0.0022	-0.014	-0.03
	(0.046)	(0.042)	(0.035)	(0.0222)
Access to safety nets	0.018	-0.052	$0.078^{*}$	-0.195***
	(0.057)	(0.038)	(0.043)	(0.043)
Access to credit	$0.257^{***}$	-0.043	$0.054^{**}$	-0.011
	(0.046)	(0.030)	(0.023)	(0.018)
Access to extension	$0.111^{***}$	$0.078^{**}$	0.0296	0.017
	(0.036)	(0.031)	(0.026)	(0.016)
Risk Aversion	0.045	-0.0299	$0.124^{***}$	-
				$0.0069^{***}$
	(0.006)	(0.034)	(0.0334)	(0.005)
Born in the village	0.045	0.145	$0.197^{***}$	
	(0.006)	(0.034)	(0.056)	
Temporary migration	$0.112^{***}$	-0.0299		
	(0.036)	(0.034)		
Death shock	-0.007	-0.0299	0.0012	$0.498^{***}$
	(0.053)	(0.034)	(0.049)	(0.054)
Parents important	0.019	$0.136^{**}$		
	(0.065)	(0.068)		
Number of observation	1141	1141	1141	1141
F-Statistics	9.28	12.15	9.92	29.18
(p-values)	0.0000	0.0000	0.000	0.0000

Table 4.11: First-Stage estimations of determinants of social capital

### Chapter 5

# 5 You Are Not Alone: Social Capital and Risk Exposure in Rural Ethiopia

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#### Abstract

We combine household panel data, weather data, self-reported health shocks and detailed social capital information to analyze how social capital can buffer some of the implications of weather and health shocks. Our results suggest that households are unable to protect themselves from both rainfall and health shocks. However, households with more social capital are able to smooth consumption. We conclude that in the absence of formal financial and insurance markets household's ability to insure consumption against shocks is largely determined by difference in social capital levels.

JEL classification: C23, D12, D71, O12,

Keywords: Consumption, Insurance, Social capital, Shocks, Ethiopia

#### 5.1 Introduction

Studies show that adverse shocks worsen food insecurity, malnutrition, and poverty in developing countries. Ethiopia is amongst the poorest developing countries prone to poverty and negative impacts of shocks. Most farm households in Ethiopia face frequent shocks in the form of drought, flood, pests, price changes and illness with little possibility of insurance. The lack of formal insurance mechanisms against unexpected shocks has led many smallholder farmers into persistent poverty and food insecurity traps (Dercon and Christiaensen, 2011; Porter, 2012). Frequent adverse shocks affect not only food security levels, but also led people to make use of a destructive and depletive way of response, since they sell assets at prices below their real value, leading to potential poverty traps.

Among frequent adverse shocks, the occurrence of rainfall shock is recognized as the single most important factor responsible for large variations in food security and poverty among smallholder farmers in many developing countries (Dercon, 2004). In a particular example of this, smallholder farmers in Ethiopia for whom agriculture forms the basis of livelihood are highly exposed to rainfall variability. As agriculture in Ethiopia is predominately rain-fed with minimal irrigation coverage, poor distribution of rainfall affects agricultural production and consequently causes food shortages (Di Falco and Chavas, 2009). Understanding the food security implications of shocks is therefore very important.

In this paper, we focus on rainfall, market and health shocks as these are the three most important shocks identified by households in rural Ethiopia (ERHS, 2009). This study explicitly captures the role social capital plays in insuring consumption against the above three important shocks in the absence of formal financial and insurance markets. This is particularly relevant as previous studies on consumption insurance in Ethiopia has largely focused on the mechanisms through which differences in initial endowments and formal government policies affect consumption and food security, paying little attention to the roles of informal social ties and social capital (Demeke *et al.*, 2011; Gertler *et al.*, 2006, Dercon, 2004; Dercon *et al.*, 2005). Controlling for social capital endowment is very important as heterogeneity in social capital is an important determinant of consumption smoothing. In this study, we adopted a broad definition of social capital as the capacity for a transaction to take place between two or more individuals by virtue of their relationship which broadly includes networks, associations and institutions. In

particular, we focus on a subset of informal social capital, namely, social network size and membership in local insurance groups  $(Iddir)^{49}$ . By focusing on the above two important social capital variables, this study not only provides new evidence on the impacts of shocks on consumption and hence food security but also examines the extent to which heterogeneity in social capital may affect households ability to insure consumption against shocks.

This paper contributes to the growing literature on consumption insurance and food security in several ways. First, we explicitly captured the role of social capital on the premise that in countries like Ethiopia where formal credit and insurance arrangements are very limited, the role of social capital in consumption smoothing will be very crucial. Second, unlike previous studies that use self-reported rainfall shocks and treat such shocks as exogenous, we used an exogenous measure of rainfall shock by using actual village level rainfall data. Third, we extended the scope of the literature by considering a shock which affects not only individual farm households but also the entire risk sharing networks. The rest of the paper is organized as follows: in section 2, we present the link between social capital and consumption smoothing. Section 3 presents data sources, shock and social capital measures and the specific econometric strategy. Section 4 presents our findings and discusses the results. Section 5 concludes with a list of open questions and an outlook on next research topics.

#### 5.2 Social capital, shocks and consumption smoothening

Households living in developing countries are often exposed to shocks (Di Falco and Bulte, 2013; De Weerdt and Dercon, 2006; Fafchamps *et al.*, 1998; Fafchamps and Lund, 2003). A growing body of literature has also examined the extent to which households are able to insure consumption against shocks (Islam and Maitra, 2012; Gertler *et al.*, 2006; Gertler and Gruber, 2002; Wagstaff, 2007; De Weerdt and Dercon, 2006; Asfaw and Von Braun, 2004; Dercon and Krishnan, 2000; Carter and Maluccio, 2003; Carter *et al.*, 2007; Townsend, 1994). In general, the aforementioned studies examined whether a household's ability to maintain consumption is affected by past shocks (Debebe *et al.*, 2013). For instance, Islam and Maitra (2012) examined the effect of health shocks on household consumption and how access to microcredit helps

<sup>&</sup>lt;sup>49</sup> *Iddirs* are informal institutions established for providing mutual aid during death of members (Dercon *et al.*, 2006).

households cope against illness in rural Bangladesh. Asfaw and Von Braun (2004), as well as Dercon and Krishnan (2000), investigated the effect of health shocks on a household's ability to smooth consumption in rural Ethiopia. They pointed out that health shocks have a statistically significant and negative effect on purchased food consumption. Similarly, De Weerdt and Dercon (2006) rejected the full risk-sharing hypothesis against health shocks in rural Tanzania. In the words of Kazianga and Christopher (2006), the general conclusion from the empirical evidence so far is that *"most households succeed in protecting their consumption from the full effects of the shocks but not to the degree required by a Pareto efficient allocation of risk within local communities."* 

However, much of the tests for risk-sharing to date are conducted at the village level (De Weerdt and Dercon, 2006). This has some drawbacks, especially in capturing the full effects of social capital, since risk-sharing through social ties may also take place between households living in different villages. The role of self-protection through social capital as a mechanism to smooth consumption against shocks have been the subject of many research debates (Fafchamps and Lund, 2003; Gertler et al., 2006). Empirical studies in many developing countries have confirmed that social capital plays a significant and positive role in enhancing consumption (Wetterberg, 2007; Tegebu, 2008; Grootaert and Narayan, 2004). Social ties have been found to help even the poorest in times of stress (Wetterberg, 2007). Often times a particular tie is successful at providing resources or decreasing risk, but this does not imply that all social ties have the same effect (Wetterberg, 2007). While it is increasingly clear that informal and formal social relationships outside the market have some effect on consumption smoothing, it is likely to be heavily contingent on the specific norm being considered, the type of resources required for insurance and the features of the social structures themselves.

In this regard, Di Falco and Bulte (2011) demonstrated that extensive networks and social capital can be associated with lower consumption showing a possible dark side of social capital. In particular, households with large stocks of social capital (such as relatives), may evade sharing obligations by accumulating durables that are non-sharable at the expense of durables that may be shared and by reducing savings on liquid assets that would be important for consumption smoothing. Similarly, Gertler *et al.* (2006) did not find any statistical relationship between social capital and a

household's ability to smooth consumption. On the other hand, Witoelar (2013) found evidence of complete consumption risk sharing within extended families among households in Indonesia. In addition, Carter and Maluccio (2003) found that South African households with more social capital were able to cope against economic shocks. In light of these mixed results, this study examines the extent to which households may rely on informal social ties and links in order to smooth consumption against shocks. The frequency of unexpected shocks and underdevelopment of formal insurance markets in Ethiopia make this analysis particularly interesting.

In the case of Ethiopia, previous studies on consumption smoothing reported the absence of full risk-sharing at the village level(e.g., Dercon, 2006; Asfaw and Von Braun, 2004; Dercon and Krishnan, 2000), albeit without taking into consideration the effect of social capital and sharing norms on a household's ability to insure consumption against shocks. Considering the role of social capital is particularly important if households are engaged in a variety of non-market and informal networks to insure themselves against shocks (Tegebu, 2008). We considered whether social capital can help households to insure consumption against both idiosyncratic and covariate shocks<sup>50</sup>. So far, the literature on consumption smoothing against covariate shocks is limited with the presumption that informal insurance functions are most effective for idiosyncratic shocks (Carter and Maluccio, 2003). It is argued that households willing to insure others against covariate shocks share similar livelihoods and living standards, leaving them unable to insure consumption fully (Carter and Maluccio, 2003). Furthermore, since covariate shocks affect all suffering households in the same way, highly localized social networks with very limited resources cannot be used to insure consumption. However, a strand of the recently growing literature, such as Carter and Maluccio (2003); Wetterberg (2007); Tegebu (2008) and Witoelar (2013), have found evidence that self-protection and risk-sharing via informal community and extended kinship networks are important in smoothing consumption against both idiosyncratic and covariate shocks. Moreover, Rosenzweig (1988) found that network ties help households insure consumption in the face of covariate shocks through implicit insurance-based cash and in-kind transfers. Similarly, Grimard (1997)

<sup>&</sup>lt;sup>50</sup> A shock is considered as idiosyncratic if the effect is confined to the household and covariate if it affects at least some other residents in the village. In the survey the following questions were used to determine a give shock as covariate and idiosyncratic: "How widespread was the shock? i) only affected my household, ii) affected some households in this village, iii) affected all households in this village, iv) affected this village and other villages nearby

found partial risk-sharing among the same ethnic groups of rural and urban households in Côte d'Ivoire.

In the case of Ethiopia, it has been shown that some forms of informal social links and organizations have an explicit insurance component against shocks. For example, Iddir provides in-kind and financial assistance in times of hardship with no to very low interest rates (Wossen et al., 2013; Wossen et al., 2015). Furthermore, some aspects of social capital and extended kinship networks help to insure consumption against shocks through moral obligation, sharing and redistribution of resources (Di Falco and Bulte, 2013). Given that formal risk-sharing mechanisms are largely limited in Ethiopia, we expect social capital to be helpful in maintaining consumption in the face of shocks. In particular, funeral insurance network (Iddir) are commonly found to be important sources of resources at times of hardship (Dercon et al., 2006; Wossen et al., 2015). In addition to providing insurance in the case of death of family members, Iddirs have been observed providing support in times of shock and offering credit to members (Hoddinott et al., 2009). The potential for these informal networks to reduce the vulnerability of membership households and provide credit in the absence of formal markets makes them highly relevant for consumption insurance. Indeed, the services they provide and the wide levels of participation in Iddirs observed in Ethiopia means they are commonly considered potential resources for consumption insurance and as providers of additional risk-mitigation services (Berhane et al., 2013; Dercon et al., 2006). Additionally, as Iddirs straddle the line of informality and formality, and as they are often composed of a mix of strong and weak ties in terms of network heterogeneity (Hoddinott et al., 2009), they represent extremely relevant points of departure for studying social capital effects on consumption insurance. The main contribution of this article is therefore to fill the research gap by investigating whether social capital measured by network size and membership to Iddir help households insure consumption against shocks.

#### 5.3 Data source and econometric strategy

#### 5.3.1 Data sources

We used data from the 2004 and 2009 rounds of the Ethiopian Rural Household Survey (ERHS)<sup>51</sup>that covers a number of villages in rural Ethiopia (Dercon and Hoddinott, 2004). The data has been collected by Addis Ababa University in collaboration with the International Food Policy Research Institute (IFPRI) and the Oxford University Center for African Economies. It covers fifteen Peasant Associations (PA) in four major administrative regions (Tigray, Amhara, Oromia and SNNPR) of the country. A total of seven rounds of data collection were conducted from 1989-2009, in which newly emerging and important issues were included in each successive round. We make use of the 2004 and the 2009 rounds of the ERHS, since social capital measurements, on which our analysis is based, are only included in these survey rounds. The survey contains detailed information on a variety of individual and household socio-economic attributes, such as food and non-food consumption, assets, social capital and household demographics. Data on food consumption was collected for more than 80 food items in the survey based on a one week-recall period. To capture consumption for infrequently consumed food items, consumption for the last four months prior to the survey time was also collected. Household food consumption was reported in terms of the total quantity consumed from own production, total value bought from the market and total value obtained from gift. The quantity of consumption from own production is converted into imputed values using prices collected at community level. We used both food and non-food<sup>52</sup> consumption values to capture the role of social capital in insuring consumption against shocks.

<sup>&</sup>lt;sup>51</sup> This data has been made available by the Economics Department, Addis Ababa University, and the Centre for the Study of African Economies, University of Oxford and the International Food Policy Research Institute. Funding for data collection was provided by the Economic and Social Research Council (ESRC), the Swedish International Development Agency (SIDA) and the United States Agency for International Development (USAID); the preparation of the public release version of these data was supported, in part, by the World Bank. AAU, CSAE, IFPRI, ESRC, SIDA and USAID

<sup>&</sup>lt;sup>52</sup> Our measure of non-food consumption excludes expenditure on health and medical care. Expenditure on health and medical care is deducted from non-food consumption. Previous studies on health shocks by Gertler, Levine and Moretti 2006; Gertler and Gruber 2002; De Weerdt and Dercon 2006; Islam and Maitra 2012; Assfaw and von Braun 2004 also used similar measurement of non-food consumption.

#### 5.3.2 Shock measures

For this study, shocks are define as adverse events that lead to a loss of household income, a reduction in consumption and/or a loss of productive assets. These include shocks such as death of family member, illness of husband, wife or family member, divorce and dispute with extended family members, drought, flooding, and large increases in food and input prices. Figure 5.1 depicts the major shocks that households faced in the past five years that lead to a loss of productive assets, a loss in household income and a reduction in household consumption. The three most important shocks that affected households in the last five years prior to the survey were drought, market shocks (rising food prices) and health shocks (illness of husband, wife or family member). In the survey, we identified that about 52% of households have reported experiencing drought shocks while 62% of households reported to have been experiencing market shocks (rising food price). A significant portion of households (29%) has also reported facing health shocks.



Figure 5.1: Percentage of households who experienced shocks in the past five years

Health shock is measured by self-reported illness of husband, wife or another person within the family. The use of self-reported health shock is not however without a problem since previous research indicated that the measurement of the illness shock variables is important in analysing the impact of illness on consumption. As pointed out by (particularly Asfaw and Von Braun, 2004; Dercon and Krishnan, 2000 using the earlier rounds of the same data set), the use of self-reported health shocks is problematic. First, there is a high measurement error since what is considered healthy is quite different among different individuals (Asfaw and Von Braun, 2004; Islam and

Maitra, 2012). Second, the problem of self-reported bias in reporting illness due to differences in education or wealth might be substantial (Dercon and Krishnan, 2000). Islam and Maitra (2012) for example found differential effects of health shocks on consumption while using short-term and longer-term measures of health shock and recommended to use long term measurements. Unlike Asfaw and Von Braun, (2004) who measured illness by self-reported health status of the head in the last 4 weeks prior to the survey, our measure of health shock corresponds to long term measures of health shock as it captures illness in the last five years that led to a serious reduction in asset holdings, caused household income to fall substantially or resulted in a significant reduction in consumption. Similar measurement was also used for the case of Tanzania by De Weerdt and Dercon (2006).

As noted by Gertler *et al.*, (2006), another potential problem with our measurement of health shocks is that they could be related to rainfall shocks. For example, a rainfall shock leading to flooding could cause malaria. A rainfall shock may also lead to a bad harvest and hence lower consumption, which in turn might lead to illness. In this case consumption shocks will be the cause of health shocks and not the other way round (De Weerdt and Dercon 2006). However, in our case the Spearman correlation coefficient between the two shocks is very low (Spearman correlation coefficient between the two is 0.05, p = 0.0000)<sup>53</sup>.

Similarly, the incidence of self-reported bias in the measurement of rainfall shocks could also introduce bias. To avoid self-reported bias in the measurement of rainfall shocks, we opted to use actual village level observed rainfall shocks instead of self-reported drought shocks. The correlation between self-reported drought shocks and the actual village level rainfall measures is 0.76, implying our measure of rainfall shocks is meaningful in capturing weather shocks. Previous studies have shown that rainfall variability affects agricultural production in general and the food security level of households in particular (Dercon, 2004; Porter, 2012). To estimate the effects of rainfall shock, we matched observed rainfall values from the weather station closest to ERHS villages with socio-economic data. Following Dercon (2004) and Porter(2012) a bad rainfall shock is defined as one in which the rainfall levels in the village in the 12

<sup>&</sup>lt;sup>53</sup> However, the problem of reverse causality between (food) consumption and health shocks may extends beyond the correlation between rainfall shocks and health shocks. This would be an important area of future research and certainly beyond the scope of this paper.

months preceding the survey fall one standard deviation below the mean. However, some villages in our study area experienced particularly high levels of drought while some villages experienced above average rainfall levels as the actual rainfall level in the 12 months preceding the survey exceeded the long-run village average levels. As a robustness check, we constructed a positive rainfall shock as one in which the rainfall levels in the village in the 12 months preceding the survey exceeded the survey exceeded the survey exceeded approximately of the survey

The final measure of shock is related to the prevalence of market shocks-especially that of food price increase. The impact of food price changes on food security is, however, not always negative. Higher food prices might be a threat to food security as many farm households are net food buyers. Yet, higher food prices may also provide an opportunity for net seller farmers. The net effect of higher food prices therefore depends on the market position of households (net buyer vs. net seller, see, Wossen and Berger, 2015).

#### 5.3.3 Social capital measures

Although a subject of much debate, empirical studies have used various ways of measuring social capital, for example through measuring local links quantified by membership in local informal and formal networks (Wossen et al., 2015). In our analysis, we focus on informal social capital measures which include: i) Network size defined as the number of individuals that a given household knows and could depend on at times of hardship and (ii) membership in funeral insurance arrangements (Iddir). The first component of social capital captures the size of the household's network. This form of social capital reflects the self-reported relationships with individuals whom a given household considers to be very important at times of hardship, from both within and outside the village. It should be stressed that extending this component non-locally is quite novel compared to the existing literature. Considering relationship beyond the village domain has important implication for consumption smoothing especially since individuals living far apart might have different livelihood strategies. However, households with large network sizes may refrain from helping others by accumulating durables that are non-sharable at times of hardship (Di Falco and Bulte, 2011). Similarly, as pointed out by Baland et al. (2011) some households with large network sizes may pretend to be poor through excessive borrowing to imply their inability to

provide financial assistance for other network members at times of hardship. If the adverse incentive effects of sharing norms are sufficiently strong, such networks may have little effect on households' ability to smooth consumption.

Our second measure of social capital is labelled as "membership in funeral insurance arrangements," which is measured from the participation of an informal arrangement locally known as "Iddir". Iddir is established for providing mutual aid during death of members (Di Falco and Bulte 2013; Dercon et al, 2006). Iddir also serves as an insurance mechanism by providing money and in-kind assistance for its members at times of hardship. There are often written rules for participation, contributions, payouts and punishments (Dercon et al., 2006). As iddirs are extremely important institutions in Ethiopia, omitting them from models of rural Ethiopia risks missing their role in smoothing production and consumption following household shocks. For a long-term model, especially one that considers outputs such as consumption smoothing, the widespread use of informal insurance is likely to have an effect on which households are able to avoid shortages when a shock in the family affects labour supply or when the costs of traditional funerals exacerbate resource constraints. Including risk-sharing networks as fixed effects estimates from econometric analysis can capture these important effects. As *iddirs* have been seen as a highly successful informal institutional arrangement, there is great interest in replicating their success elsewhere. The conditions for building a successful Iddir, however, are not immediately clear. While statistical analysis can show what factors influence current levels of participation, the use of panel data could begin the process of considering what factors are necessary for risk-sharing networks that resemble *iddirs* to arise in the first place. The contribution of this paper would therefore be a significant one, in that it would represent a first step at explaining how well structure networks like *Iddir* may affect consumption smoothing behaviours in developing countries.

#### 5.3.4 Econometric strategy

We first start our estimation strategy focusing on the effect of shocks on household's ability to smooth consumption. We then introduce a framework to capture the effect of social capital on household's ability to insure consumption against unexpected shocks. As mentioned above, the effect of shocks on household's ability to smooth consumption is examined following the approach of Grootaert and Narayan (2004).

We address this relationship in the context of a simple econometric specification as follows.

$$\Delta \ln \left(\frac{C_{ijt}}{H_{ijt}}\right) = \alpha_0 + \beta S_{ijt}^h + \pi S_{ijt}^m + \gamma S_{jt}^r + \vartheta X_{ijt} + \varepsilon_{ijt}$$
(18).

Where  $C_{ijt}$  is the real consumption of household *i* in village *j* at time *t*.  $H_{ijt}$  measures household size. Similarly,  $S_{ijt}^h$  and  $S_{ijt}^m$  captures health and market shocks faced by household *i* in village *j* at time *t* while  $S_{jt}^r$  measures rainfall shocks faced by village *j* at time *t*.  $X_{ijt}$ , includes a vector of household and village level variables. Next, we test the effects of social capital on households ability to insure consumption against unexpected shocks following the approach of Dercon (2004); Gertler *et al.* (2006); De Weerdt and Dercon (2006) and Islam and Maitra (2012). Formally the empirical specification of the risk sharing model is presented as follows:

$$\Delta \ln \left(\frac{C_{ijt}}{H_{ijt}}\right) = \alpha_0 + \beta S_{ijt}^h + \pi S_{ijt}^m + \gamma S_{jt}^r + \theta Z_{ijt} + \vartheta X_{ijt} + \varepsilon_{ijt}$$
(19).

 $Z_{ijt}$  measures changes in social capital. The above equation is the most widely used econometric specification of consumption insurance. If complete insurance against shocks exist, we expect  $\beta = 0$   $\pi = 0$  and  $\gamma = 0$ . In the above specification, social capital can be potentially endogenous since unobservable factors influencing changes in social capital may also influence consumption directly. Wealthier households, for instance, might have more opportunities to possess large network size as well as better consumption smoothing ability compared to poorer households. Endogeneity of social capital in the above specification further implies that if the correlation between consumption levels and social capital is sufficiently high, then estimated results will become biased. The availability of panel data can, obviously, help to deal with this problem. Fixed effect specification provides consistent parameters estimate in the presence of correlation between the time invariant unobservable and social capital variables. In particular, the use of fixed effect sweeps out the effects of any timeinvariant factors which determines both social capital formation and ability to smooth consumption (De Weerdt and Dercon, 2006; Gertler et al., 2006). Moreover, the inclusion of a time dummy can control for elements of heterogeneity that are common

to all the areas of the study. There still could be, however, some correlation, between time varying unobservable and the variables of interest.

Our identification strategy is therefore to implement an Instrumental Variable (IV) regression approach. Finding suitable instruments is notoriously challenging. Previous studies have shown that people who were born and raised in the same village tend to have more extensive social connections and are characterized by stronger social ties (Wossen et al, 2015; Demeke, 2015). We therefore used the dummy variable of whether the household head was born in this village or not and the number of journey's the household head made outside the village as an instrument for the social capital variable network size. We hypothesize that these variables would affect household's ability to smooth consumption only through their effect on network formation. As such, these variables are closely related to the formation of local networks but do not directly affect consumption. One factor that is closely related to the formation of *Iddir* in the Ethiopian context is trustworthiness. In particular, Dercon et al., (2006) showed that generally Iddirs are quite inclusive but membership is often based on trust. In particular, households that trust others in their village are more likely to be members of *Iddir*. As a result, we used trustworthiness as a potential instrument for *Iddir*. This variable directly affects membership to *Iddir* but not consumption ability smoothing directly. Trust is measured based on the respondent's perception of trustworthiness of people in the village. Trust in people is captured as a dummy variable with a value of one if respondents think that people in general are trustworthy and zero otherwise.

In order to test if households with better social capital levels are able to buffer the consumption implications of different types of shocks, we extend specification (2) by adding an interaction term between shocks and social capital measures<sup>54</sup>.

$$\Delta \ln \left(\frac{C_{ijt}}{H_{ijt}}\right) = \alpha_0 + \beta S_{ijt}^h + \gamma S_{jt}^r + \pi S_{ijt}^m + \rho \left(S_{ijt}^h \times Z_{ijt}\right) + \varphi \left(S_{jt}^r \times Z_{ijt}\right) + \theta Z_{ijt} + \vartheta X_{ijt} + \varepsilon_{ijt}$$
(20).

The coefficient of interaction between social capital and the shock variable ( $\rho$ ) and ( $\varphi$ ) represents the effect of social capital on a household's ability to insure consumption

<sup>&</sup>lt;sup>54</sup> Measuring the interaction effect between market shocks and social capital is beyond the scope of this paper. Theoretically, market shocks may not adversely affect food security and hence the role that social capital may play cannot be specified a priori.

against shocks. If  $\rho > 0$  and  $\varphi > 0$ , social capital will have a positive role in insuring consumption against shocks. According to Nizalova & Murtazashvili (2014), OLS estimates of the coefficient on the interaction term between the exogenous variable (rainfall shock) and the endogenous variable (social capital) should be consistent even without implementing an IV strategy. In our empirical specification (equation 3) of the interaction between rainfall shock and social capital variables, the OLS estimates of  $\varphi$ and  $\rho$  should therefore be consistent even in the presence of endogeneity bias from  $Z_{ijt}$  as far as  $S_{jt}^r$  is strictly exogenous.

#### 5.3.5 Descriptive statistics

Definition and descriptive statistics for social capital and other control variables used in the regression analysis is presented in Table 5.1.

	2009		2004	
Variable	Mean	SD	Mean	SD
Demographic characteristic				
Age (Age of the household head in years)	54.5	15.3	51.8	15.3
Education (1= household head is literate)	0.53	0.49	0.37	0.48
Household size	5.9	2.48	5.8	2.43
Assets and resource constraints				
Farm size (in ha)	0.4	1.15	1.6	1.9
Access Variables				
Access to safety nets(1= has access to safety net)	0.23	0.42	0.44	0.49
Access to credit (1= has access to credit)	0.62	0.48	0.53	0.49
Access to Off-farm (1= has access)	0.47	0.52	0.36	0.41
Outcome Variables				
Non-food consumption(Birr/monthly)	240.1	312.9	109.6	161.1
Food consumption(Birr/month)	817.9	639.3	419.4	417.9
Total consumption(Birr/month)	1058	822.9	528.2	503.2
Real per capita food consumption(Birr/month)	51.1	62.4	70.4	45.3
Social capital Variables				
Iddir(1= member to Iddir)	0.85	0.35	0.81	0.39
Total network size	14.94	15.16	10.29	10.69
Weather Variables				
Mean rainfall (mm)	993	304.2	1210	288.5
Anomaly Index	-0.73	0.89	0.17	1.15

Table 5.1: Variable list and descriptive statistics

In the survey, the mean number of individuals that the household perceives to be very important at times of hardship increased from 10.29 individuals in 2004 to 14.94

individuals in 2009. On the other hand, membership to *Iddir* increases marginally from 81% to 85%. In addition, Table 5.1 reports the average monthly food, non-food and total consumption of each respondent. Average household monthly food consumption varies from 419 birr in 2004 to 817 birr (\$45) in 2009. Like in many other developing countries, food consumption accounts for about 78% of the total household consumption. Similarly, total consumption increased from 528 birr in 2004 to 1058 birr in 2009. In order to make a reasonable comparison across rounds, we followed the approach of Tefera *et al.* (2012) and converted all nominal expenditures into real expenditures by deflating each price variable with a weighted price index using the 1994 survey period as a reference. In the regression analysis, we used real per capita consumption instead of nominal expenditure values.

In terms of independent variables, we included several household characteristics such as age which captures the effects of experience in dealing with shocks and educational attainment. Average household size varies from5.8 members in 2004 to 5.9 members in 2009 while the proportion of literate households increased from 37% in 2004 to 53% in 2009. To capture the wealth (income) effect we include non-farm income as a proxy for the capacity to cope shocks. In addition, we include institutional and access variables such as access to credit and access to safety nets because of their relevance for consumption insurance especially when a given shock affects the entire risk sharing network.

#### 5.4 Results

#### 5.4.1 Social capital and consumption smoothing

We first present the result of a baseline regression where we considered the empirical question of whether households are able to withstand the effect of shocks. Next we present the results of our regression analysis undertaken to examine whether social capital and sharing norms have any effect on household's ability to insure consumption against shocks. The effects are separately presented for food consumption (Table 5.2), non-food consumption (Table 5.3) and total consumption (Table 5.4). Moreover, in each specification, we first did a baseline regression without including social capital variables and household characteristics as regressors. We then included social capital variables as additional controls along with the interaction terms of social capital and shocks to analyse the effects of social capital.

Our first result is presented in Table 5.2 (Model 1) where we estimated the effect of shocks on food consumption without including social capital and other controls. As expected, rainfall shock has a negative and statistically significant effect on household food consumption growth implying the inadequacy of self-coping mechanisms against this type of shock. This finding is particularly relevant in the context of Ethiopia as agriculture is predominately rain-fed with limited irrigation coverage. Similar results have also been reported by Dercon *et al.* (2005); Porter (2012) and Demeke *et al.*, (2011).

Our results further show that health and market shocks affect food consumption growth negatively. This result is in tandem with Dercon et al. (2005)<sup>55</sup>. Next, we examined whether households with better social capital are able to smooth food consumption against both covariate and idiosyncratic shocks. We found three interesting results. First, the interaction term between rainfall shock and network size variable is positive while the direct effect of rainfall shock is negative implying some mitigating effects of social ties. Second, the interaction term between rainfall shock and network size functions of Iddir. Third, the interaction term between health shock and network size variable becomes positive and statistically significant while the direct effect of health shock is negative. This implies that reduction in food consumption due to health shocks is compensated for by gifts from others in the network. These results underscore the important insurance roles of social capital against the implications of shocks.

Our result stands in contrast to earlier studies, which tend to document little support for the hypothesis that social capital helps households to insure consumption against health shocks (e.g. in Indonesia (Gertler *et al.*, 2006). Our results are, however, not surprising for Ethiopia, since strong family attachments and altruism are essential parts of traditional Ethiopian life. In particular, Debebe *et al.* (2013), using the same data set, pointed out that households tend to rely on asset sales (mainly livestock) and borrowing from relatives and neighbours when facing health shocks. In addition, membership to *Iddir* implies commitment to specific normative behaviour, such as helping other members, due to social and peer influence. Model 3 in Table 5.2 presents

<sup>&</sup>lt;sup>55</sup> Using the 2004 rounds of ERHS data, Dercon et al. (2005) reported that experiencing health shock reduces consumption growth by 9%.

IV-regression results. In terms of the effect of social capital, we found consistent results in terms of the direction and the magnitude of effects in our IV specification.

Variables	No Controls	With Social capital	With IV	With interaction terms	All controls
	1	2	3	4	5
Rainfall shock	-0.144***	-0.152***	-0.1665***	-0.21***	-0.186***
	(0.048)	(0.047)	(0.048)	(0.069)	(0.07)
Health shock	-0.114**	-0.115***	-0.112**	-0.39***	-0.392***
	(0.052)	(0.05)	(0.051)	(0.113)	(0.114)
Market shock	-0.109**	-0.099**	-0.116***	-0.091*	-0.09*
	(0.049)	(0.048)	(0.051)	(0.048)	(0.048)
Network size		$0.0076^{**}$	0.0092***	0.0049**	0.005**
		(0.0012)	(0.003)	(0.0019)	(0.0019)
Membership to Iddir		$0.467^{***}$	$0.477^{**}$	0.41***	$0.417^{***}$
		(0.087)	(0.22)	(0.091)	(0.094)
Rainfall shock*Iddir				0.459***	0.433***
				(0.119)	(0.12)
Rainfall shock* Network size				0.0003	0.0004
				(0.0044)	(0.0044)
Health shock*Iddir				0.172	0.176
				(0.121)	(0.124)
Health shock* Network size				$0.0119^{**}$	$0.0117^{***}$
				(0.0038)	(0.0038)
Time dummy	Yes	Yes	Yes	Yes	Yes
$\mathbf{R}^2$	0.42	0.447	0.45	0.46	0.46
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000
Ν	1888	1888	1888	1888	1888

Table 5.2: Food consumption growth and shocks

The dependent variable is change in log real food consumption between survey waves of 2004 and 2009. Robust standard errors are reported in parentheses. \* Significance at the 10% level. \*\*\* Significance at the 5% level. \*\*\* Significance at the 1% level. List of controls: age, education, farm size, off-farm, access to safety net and access to credit.

Overall, our results reaffirm that social capital matters in insuring food consumption against shocks. Moreover, it is reassuring to observe positive signs for all our social capital variables as the empirical relevance of each effect is not only related to the significance, but also to the sign of the impact estimated for different social capital indicators. In this regard, our results clearly support the hypothesis that a higher level of social capital is associated with better household food consumption levels. However, the evidence presented on food consumption smoothing against rainfall shocks must be taken with caution. We did not consider the possibility of consumption
smoothing against complete collapse, such as drought, which affects not only individual farm households but also the whole risk sharing/social capital network. However, the results here are informative in the sense that current level of rainfall shocks could be insured through informal social capital and networks. In fact, using data on network-wide shocks we document the absence of insurance against shocks which affect the entire risk sharing networks (see, Robustness section).

Next we test the full risk-sharing hypothesis using non-food consumption. We used a parsimonious specification as before where we used standard controls as regressors at first and then introduced our social capital variables as well as their interactions with the shock variables. Our results for non-food consumption are presented in Table 5.3. We found that the effect of rainfall, market and health shocks on non-food consumption growth is insignificant but negative, implying that we cannot reject the hypothesis that non-food consumption is at least partially insured. Similar results were also reported by De Weerdt and Dercon (2006) and Islam and Maitra (2012), for the cases of Tanzania and Bangladesh respectively. In terms of social capital, neither the interaction term between shocks and network size variable nor the interaction term between *Iddir* and shocks becomes significant when considering non-food consumption. This result suggests the absence of risk sharing arrangements for non-food consumption through social capital.

Variables	No	With	With	All
	Controls	Social	interaction	controls
		capital	terms	
	6	7	8	9
Rainfall shock	-0.0019	0.0014	-0.0058	-0.0053
	(0.0041)	(0.0027)	(0.0038)	(0.0038)
Health shock	0.0045	0.0028	0.008	0.008
	(0.003)	(0.0022)	(0.01)	(0.0107)
Market shock	0.0014	0.00076	0.0008	0.0005
	(0.0033)	(0.0025)	(0.0024)	(0.0025)
Network size		-0.0007***	-0.0009***	-0.0009***
		(0.00014)	(0.00016)	(0.00016)
Membership to Iddir		$0.114^{***}$	$0.112^{***}$	0.109***
-		(0.013)	(0.0133)	(0.0133)
Rainfall shock*Iddir			0.0078	0.0072
			(0.007)	(0.0066)
Rainfall shock* Network size			0.0007	0.00068
			(0.0022)	(0.0022)
Health shock*Iddir			-0.0087	-0.0085
			(0.0106)	(0.0106)
Health shock* Network size			0.00019	0.00017
			(0.0003)	(0.00032)
Time dummy	Yes	Yes	Yes	Yes
Prob > F	0.0000	0.0000	0.0000	0.0000
Ν	1	1888	1888	1888

Table 5.3: Non-food consumption growth and shocks

The dependent variable is change in log real non-food consumption between survey waves of 2004 and 2009. Robust standard errors are reported in parentheses. \* Significance at the 10% level. \*\* Significance at the 5% level. \*\*\* Significance at the 1% level. List of controls: age, education, farm size, off-farm, access to safety net and access to credit.

Finally we presented our estimated results using total consumption. We followed a similar strategy as before, where we introduced control variables at first and then our social capital variables along with the relevant interactions to estimate the role of social capital. The results are presented in Table 5.4 below. Our first result shows that total consumption is not insured against shocks. The results are quantitatively similar to that of food consumption, albeit different to that of non-food consumption. This, however, is not surprising, since food consumption accounts for nearly 80% of the total consumption in the survey. In terms of social capital roles, the results are numerically similar in terms of the magnitude and direction of the effects to that of food consumption.

Variables	No Controls	With	With IV	With	All controls
		Social		interaction	
		capital		terms	
	10	11	12	13	14
Rainfall shock	-0.137***	-0.157***	-0.148***	-0.189***	-0.166**
	(0.0499)	(0.048)	(0.048)	(0.069)	(0.07)
Health shock	-0.12**	-0.118**	-0.119**	-0.396***	-0.401***
	(0.053)	(0.051)	(0.05)	(0.116)	(0.118)
Market shock	-0.112**	-0.115**	-0.10**	$-0.092^{*}$	-0.091*
	(0.05)	(0.051)	(0.048)	(0.048)	(0.048)
Network size		$0.011^{***}$	$0.0091^{***}$	$0.0069^{***}$	$0.007^{***}$
		(0.0034)	(0.002)	(0.0019)	(0.002)
Membership to Iddir		$0.504^{***}$	0.603***	$0.543^{***}$	$0.55^{***}$
		(0.22)	(0.0902)	(0.094)	(0.097)
Rainfall shock*Iddir				$0.45^{***}$	$0.424^{***}$
				(0.122)	(0.123)
Rainfall shock* Network size				-0.00137	-0.0013
				(0.0044)	(0.0044)
Health shock*Iddir				0.181	0.185
				(0.123)	(0.126)
Health shock* Network size				$0.0116^{***}$	$0.0114^{***}$
				(0.0039)	(0.0039)
Time dummy	Yes	Yes	Yes	Yes	Yes
$\mathbf{R}^2$	0.41	0.449	0.44	0.46	0.46
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000
Ν	1888	1888	1888	1888	1888

Table 5.4: Total consumption growth and shocks

The dependent variable is change in log real total consumption between survey waves of 2004 and 2009. Robust standard errors are reported in parentheses. \* Significance at the 10% level. \*\* Significance at the 5% level. \*\*\* Significance at the 1% level. List of controls: age, education, farm size, off-farm, access to safety net and access to credit.

#### 5.4.2 Robustness checks

While, examining the role of social capital, we did not consider the possibility of consumption smoothing against complete collapse, such as drought which is a prominent feature of Ethiopia. Here we extend our analysis by considering a network-wide shock which affects not only individual farm households but also the whole risk sharing/social capital networks. Note that, extreme rainfall shock is measured at village level and hence does not affect the whole risk sharing network as *Iddir* membership and network size were not strictly restricted at village level. As a result, we used a sub-sample of our data in which membership for *Iddir* and *size of network* measured at village level to measure how social capital my buffer the implications of shocks that affect the whole risk sharing network. Such analysis is extremely useful for designing appropriate safety net policies. Interestingly, we found that consumption

(food, non-food and total) is not insured through social capital when a shock affects the whole risk sharing network. Moreover, we show that formal policy interventions such as access to consumption credit and safety nets are the only effective ways of insuring consumption. Self-coping mechanisms through livestock also appears to be effective in insuring consumption when a shock affects the whole risk sharing network.

Table 5.5: Robustness check using network-wide shocks

	Food	Non-food	Total
	consumption	consumption	consumption
Variables	15	16	17
Network-wide rainfall shock	-0.44***	-0.021***	-0.59***
	(0.0092)	(0.0011)	(0.0062)
Size of network	0.00014	0.0023	0.034
	(0.0023)	(0.0044)	(0.06)
Membership to Iddir	0.0462	-0.432	0.024
	(0.0541)	(0.219)	(0.032)
Network-wide rainfall shock *size of network	-0.0142	-0.0324	-0.0532
	(0.0532)	(0.055)	(0.0871)
Network-wide rainfall shock *Iddir	-0.048	-0.341	-0.143
	(0.059)	(0.233)	(0.139)
Access to safety nets	$0.46^{***}$	$0.129^{***}$	$0.309^{***}$
	(0.018)	(0.007)	(0.098)
Access to credit	0.356***	$0.163^{***}$	$0.243^{***}$
	(0.021)	(0.014)	(0.0131)
Access to safety nets* Network-wide rainfall shock	$0.21^{***}$	0.103***	$0.189^{***}$
	(0.043)	(0.003)	(0.037)
Access to credit* Network-wide rainfall shock	0.134**	$0.092^{***}$	$0.119^{**}$
	(0.05)	(0.0019)	(0.04)
Time dummy	Yes	Yes	Yes
Ν	460	460	460
Prob > F	0.0000	0.0000	0.0000

Robust standard errors are reported in parentheses. \* Significance at the 10% level. \*\* Significance at the 5% level. \*\*\* Significance at the 1% level. List of controls: age, education, farm size, off-farm.

The next section then probes the robustness of our results by considering positive rainfall deviations from the long term mean as a measure of rainfall shock. In our previous analysis, we defined bad rainfall shock as one in which the rainfall levels in the village in the 12 months preceding the survey fall one standard deviation below the mean. However, some of the villages in our study area experienced positive (too much) rainfall shocks. In our main analysis, we examined only negative rainfall shock as it has been reported by Dercon *et al.* (2005) that only bad rainfall shocks cause consumption downfalls. Moreover, according to ERHS (2009), only about 8%

mentioned flooding and too much rainfall as causing a significant decline in income. Nonetheless, as a robustness test we constructed a positive rainfall shock when total rainfall levels in the village in the 12 months preceding the survey exceeds one standard deviation above the long term mean. Our results are presented in Table 5.6 below. We found that such shocks have no significant negative effect on consumption growth.

Table 5.6: Consumption growth and positive rainfall shocks

	Food consumption	Non-food consumption	Total consumption
Variables	18	19	20
Positive rainfall shock	0.045	-0.0009	0.048
	(0.031)	(0.0019)	(0.032)
Time dummy	Yes	Yes	Yes
Ν	1814	1814	1814
$\mathbf{R}^2$	0.41	0.16	0.40
Prob > F	0.0000	0.0000	0.0000

Standard errors are reported in parentheses. \* Significance at the 10% level. \*\* Significance at the 5% level. \*\*\* Significance at the 1% level.

In our third robustness check, we estimated the effect of shocks using a different measure of food security indicator besides growth in food consumption. In particularly, we examined the effect of shocks on calorie intake. Our results are reported in Table 5.7. We found that food consumption growth (in calorie) is negatively affected by shocks.

Table 5.7: Consumption growth using calorie intake

	Food
	consumption
Variables	18
Rainfall shock	-0.120****
	(0.039)
Health shock	$-0.0797^{*}$
	(0.041)
Market shock	-0.081***
	(0.04)
Time dummy	Yes
N	1885
$\mathbf{R}^2$	0.37
Prob > F	0.0000

Standard errors are reported in parentheses. \* Significance at the 10% level. \*\* Significance at the 5% level. \*\*\* Significance at the 1% level.

Our final robustness check captures the effect of household level idiosyncratic rainfall shocks. In the shock measurement section, we argued that the problem of self-reported bias in the measurement of rainfall shocks introduces measurement error in our estimation. Measurement errors in self-reported rainfall shocks arise since the definition of a shock may differ from household to household within a given village or across villages due to unobserved and observed differences among households. Even though, the use of fixed effect, sweeps out any time-invariant sources of bias, endogeneity bias may still persist as a result of time variant sources of bias. This is quite obvious in the data as households within the same village reported the occurrence of drought shocks differently. This measurement error in self reported rainfall shock can arise due to difference in experience, education, type of crops grown by the farmer etc. However, by using village level rainfall shocks, we may fail to capture household level effects of drought as we did not control for farm level diversification strategies such as irrigation due to lack of data. The result shows that idiosyncratic rainfall shocks have negative effect on consumption growth (food, nonfood and total).

Variables	Food expenditure	Non-food	Total expenditure
		expenditure	
	1	2	3
Idiosyncratic rainfall shock	-0.133**	0.0023	-0.135**
	(0.056)	(0.0035)	(0.057)
Time dummy	Yes	Yes	Yes
Prob > F	0.0000	0.0000	0.0000
Ν	1888	1888	1888

Table 5.8: Consumption smoothing and idiosyncratic rainfall shock (using self-reported rainfall shocks)

Standard errors are reported in parentheses. \* Significance at the 10% level. \*\* Significance at the 5% level. \*\*\* Significance at the 1% level.

# 5.5 Conclusion

The paper provides an empirical analysis of the impact of different social capital indicators on household's ability to smooth consumption in Ethiopia, a very shock prone country. In particular, the interaction effect between different social capital indicators and shocks experienced by farm households were investigated. At the methodological level, we used data from 2004 and 2009 rounds of the Ethiopian Rural Household Survey (ERHS) to estimate different panel model specifications explaining the determinants of consumption smoothening. In particular, we estimated a fixed

effect panel model to examine the empirical question of whether households with high levels of social capital are better-off. Moreover, we undertook an IV-estimation, instrumenting the social capital indicators for controlling potential endogeneity problems. In addressing the effect of social capital and sharing norms on household's ability to insure consumption against shocks, we employed the standard risk sharing econometric specifications.

Based on undertaken econometric analyses, we draw the following conclusions: First, consistent with previous findings, we found that shocks affect household food security adversely. Second, in terms of household's ability to smooth consumption, we found that households are unable to protect themselves from both covariate and idiosyncratic shocks. Our results further show that households with better social capital are able to smooth consumption. In particular, we found an empirical confirmation that social capital enables households to smooth consumption in Ethiopia where formal credit markets are limited. However, further research should examine how qualitative differences between these types of social network ties may affect consumption smoothing.

Further, our result suggest that when a shock affects the entire risk sharing network, informal-coping mechanisms through social capital strategies will be ineffective in shielding households against the implications of shocks. As such, policy interventions designed to improve the asset-base of farm households will be very important. In addition, well-targeted consumption credits, such as food for work and other production-oriented safety nets, will be important in reducing the impacts of shocks. This is particularly the case as access to credit and safety nets become important mechanisms for consumption smoothing when a shock affects the entire risk sharing networks.

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# Chapter 6

# **6** General Discussion and Policy Implications

This chapter provides a short discussion of the main results of this thesis which are summarized as follows:

- ✓ Climate and price variability adversely affects household food security in Ethiopia and Ghana.
- ✓ Self-coping mechanisms are important but not enough to shield households from the impacts of variability.
- ✓ Policy interventions are important when provided in packages. A single course of intervention has only marginal benefits.
- ✓ Households differ in terms of vulnerability and responsiveness to policy interventions and hence consideration of best fits instead of one size fits all intervention is crucial.
- ✓ Examining the distributional aspects of variability requires methods such as ABM that captures farm level costs and benefits as well as interactions and feedbacks.
- ✓ Social capital is critical for maintaining food security at times of shocks and for the adoption of risk mitigating strategies.

Detailed discussion of the above main results is provided in the following main sections.

# 6.1 Effect of climate and price variability

This thesis argues that the pre-dominantly used approach of regressing a measure of year to year variation of weather and price data in the spirit of Ricardian approach may not capture the full distribution of the effects of climate and price variability on household income and food security due to unobservable heterogeneity. By combining extensive time-series price data as well as exogenous variation in rainfall (crop damage) during the growing season, this thesis estimated the distribution of the effects of climate and price variability using a novel ABM. In capturing, the combined effects of climate and price variability, we considered co-variation in price and climate from observed data. In both Ethiopia and Ghana, we established a correlation between

rainfall and price from survey data, and hence both climate and price variability effects were modelled considering such co-variation. Table 6.1 summarizes the results of chapter 2 and 3 focusing on the impact of climate and price variability on household income. The result clearly shows that households in both Ethiopia and Ghana are unable to buffer the impacts of climate and price variability on their own, and hence adaptation options are necessary. For example, average household income declined by about 5% in Ethiopia while income declines by about 20% in Ghana.

Table 6.1: Effects of climate and price variability in Ethiopia and Ghana

Average effects on household income	Ethiopia	Ghana
Price and climate variability effect (%)	-5	-5

In order to design a best-fit intervention instead of a 'one size fits all' approach, it is important to capture the distribution of effects at the household level. Our simulation results on the effects of climate and price variability across different households emphasizes this point. Figure 6.1 shows the effect of climate and price variability in Ethiopia and Ghana at household level. The figure in the left panel shows effects at household level in Ethiopia ranked by baseline income in the counterfactual scenario while the figure in the right panel shows effects at household level for Ghana. The results shows that, on average effects are negative for most farm households. However, poorer households tend to be more vulnerable to the effects of climate and price variability in both countries.



Figure 6.1: Average effect of climate and price variability on household income: Left panel shows effects in Ethiopia while the right panel shows effects in Ghana

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The next policy relevant question in the context of these heterogeneous effects of climate and price variability is that, if farm households in Ethiopia and Ghana are largely vulnerable to the effects of variability, will autonomous and planed adaptation strategies become equally effective in Ethiopia and Ghana? The next section summarizes the effectiveness of adaptation options and policy interventions.

# 6.2 Effectiveness of coping and adaptation options

In terms of coping strategies, our simulation results show that the effects of climate and price variability on consumption are considerable, but smaller, for those households with relatively large livestock endowments in Ethiopia and Ghana. This finding confirms that households use livestock wealth as a buffer for consumption smoothing under climate variability. In addition to livestock, we also found that farm households with a large plantation area of eucalyptus were able to cope with the effects of variability in Ethiopia. Therefore, our results suggest that 'self'-coping strategies are important, although not sufficient, and should be complemented with appropriate policy interventions.

In terms of policy interventions, we found significant differences in income and food security levels between those farm households that implemented the policy options and those that did not. The great strength of our simulation experiment is its agent-based nature, which enables exploration of how effects are distributed across farm households in Ethiopia and Ghana. Table 6.2 summarizes the simulation results of chapter 2 and 3 on the distributional aspects of policy interventions considering the following key policy indicators (i) income – average change of income compared to the baseline without any variability; (ii) food security – share of agents failing to meet their minimum food consumption expenditure; (iii) heterogeneity of impact – here measured as the share of agents able to maintain or increase their income as compared to the baseline without any variability.

Indicator	Case study	Without variability	With climate and price variability	Credit	Credit plus fertilizer subsidy	Credit plus off- farm	Credit plus fertilizer subsidy plus ideal technical change
Change in	Ethiopia	n/a	-5	0.88	3	n/a	4.2
average income (%)	Ghana	n/a	-21.5	17	n/a	29.3	n/a
Food	Ethiopia	35.3	36.5	36.3	36	n/a	35.9
insecurity (%)	Ghana	60.8	69.7	37.5	n/a	24.7	n/a
Share of winners (%)	Ethiopia	n/a	16.5	74.4	88	n/a	87
	Ghana	n/a	8.3	77.3	n/a	88.9	n/a

Table 6.2: Heterogeneous impacts of policy interventions

The simulation results clearly show that poor farm households are vulnerable to climate and price variability, under which they suffer food insecurity, while a small group of wealthy farms are better off due to higher prices, achieved when selling crops. For instance, only, 18.3% and 8.3% of agents were able to maintain or increase their income under climate and price variability compared to the situation of no climate and price variability in Ethiopia and Ghana respectively. Policy interventions aimed at promoting new crop varieties appear to be effective if implemented under optimal conditions (that is, if innovation diffusion could be sped up along with credit and fertilizer subsidies) for the case of Ethiopia. For the case of Ghana, if credit is provided along with the current irrigation facilities, significant changes can be achieved in terms of food security and income. The results further underscored the need for improving adaptive capacity, as a large proportion of farm households were unable to shield themselves against the impacts of price and climate variability.

#### 6.3 On considering social capital and informal links effects

While considering the impacts of climate and price variability in Ethiopia and Ghana, we have not explicitly addressed the role of social capital and informal social links as a mechanism to cope and adapt to the impacts of climate and price variability. However, a considerable body of literature on many developing countries has shown that social capital and informal social links are crucial and worth consideration. As a result, in chapter four and five of this study, we considered the effects of such links on

household wellbeing and the adoption of technologies for reducing the impact of climate variability, taking Ethiopia as a case study. Unfortunately, due to the lack of data, we were not able to provide a comparative study on the effects of such links between Ethiopia and Ghana. However, follow-up research will help to clarify to which extent the results from Ethiopia are implicative for Ghana as well.

Our results on the roles of social capital and informal social links on a household's ability to adopt risk mitigating land management strategies and as insurance against covariate and idiosyncratic shocks show the importance of incorporating informal social links and social capital in economic analysis of smallholders in developing countries. We found that social capital is an important determinant for the adoption of innovative land management practices. In particular, we found that social capital enables farmers to alleviate labour shortages via labour exchange arrangements, as well by relaxing liquidity constraints in the absence of formal credit markets. The study reveals that low adoption rates of land management techniques for reducing climate variability impacts are caused by a combination of individual action problems, mainly due to limited access to capital, labour and the information market, as well as risk aversion.

In terms of the role that social capital and informal social links play as a coping mechanism for the impacts of climate variability, we found a number of patterns that suggest an important role for social capital in mitigating the influence of shocks. In particular, based on the undertaken econometric analyses we found that both rainfall and health shocks affect household welfare adversely (which is in line with our simulation experiment). Further, in terms of the household's ability to smooth consumption, we found that households are unable to protect themselves from both rainfall and health shocks (which is also in line with our simulation experiment). Finally, our results show that households with better social capital are more likely to smooth consumption and accumulate livestock, highlighting the need for considering such effects and the role of social capital in a simulation model.

# 6.4 Contributions

This thesis has two main contributions. The first is methodological and the second is empirical. Methodologically, the study is the first to develop and employ an agentbased modelling approach for quantifying climate and price variability effects in the context of Ethiopia and Ghana. This is quite novel compared to the existing climate variability research which focuses on macro level impacts. In addition, unlike, previous studies this thesis considered the linkages between crop and livestock sub-systems, the "recursive" nature of livestock keeping and the key role that livestock plays as a coping mechanism. The approach employed in this thesis further captures non-separability of production and consumption decisions by prametrizing consumption, innovation and production behaviour of households through microeconomics techniques. In examining how social capital and informal risk-sharing networks affect household wellbeing and the adoption of risk mitigating land management practices, the study employed novel micro-econometric techniques that account for the potential endogeneity of social capital.

The second contribution is empirical. By combining disaggregate socio-economic and climate/crop data, the study quantified the impacts of climate variability on food security and poverty at household level. In doing so, the study provides potential entry points on how specific adaptation strategies and policy interventions, especially those related to the promotion of improved credit, adoption of improved seed varieties, fertilizer subsidy and off-farm employment may affect the distribution of household food security and poverty outcomes. Through the use of MPMAS, this study was also able to analyze the role of livestock and eucalyptus production, the distributional aspect of effects, and heterogeneity in responsiveness to the policy interventions as well as interaction among households for adoption of adaptation mechanisms. Finally, this thesis fills the research gap on the roles of social capital by investigating the differential effects of the type and size of social capital on household wellbeing and technology adoption.

### 6.5 Limitations and model extensions for future research

### 6.5.1 Capturing informal social network effects

There is a growing recognition in the development community that vulnerability to adverse shocks is a defining characteristic of poverty, with the world's poor facing thin insurance possibilities and little possibility for hedging against risk. In particular, capturing and examining the extent to which informal risk-sharing social networks contribute to maintaining a household's consumption when challenged by shocks is an important issue to assess under climate variability. Our econometric analysis in Chapter 5 also underscores this argument. As implemented currently, some functions of social network effects are captured, especially on adoption of new agricultural technologies. However, the role of such informal networks and links to insure consumption against climate variability is not yet adequately captured. Our analysis of climate variability impacts clearly indicated that informal social networks are particularly important in insuring consumption against idiosyncratic and covariate shocks. As such, capturing the role of such networks in the current version will be important. As it is now, we may overestimate the impacts if we fail to consider the ability of households to use their informal networks as a safety net in the face of shocks.

The other important aspect of including social network effects is to capture what is commonly called "divergent adaptation". In the words of Snorek et al. (2014) "Adaptation is divergent when one user or group's adaptation causes a subsequent reduction in another user or group's adaptive capacity in the same ecosystem." This is particularly important, as autonomous adaptation using environmental goods such as income from forest resources and fire wood collection are common means of adaptation in many developing countries, including Ethiopia and Ghana.

# 6.5.2 Explicit consideration of risk

Risk is an integral part of decision making in Ethiopia and Ghana. In fact, a growing body of literature (see, Groom *et al.*, 2011; Koundouri *et al.*, 2006; Kumbhakar and Tveterås, 2003) link risks aversion with a low level of technology adoption. Similarly, Di Falco (2014) examined the causal impacts of climate variability on risk aversion and found that farm households who are frequently exposed to rainfall variability are more likely to become more risk averse. Dercon and Christiaensen (2011) also documented similar results for the case of Ethiopia. If climate variability increases risk aversion, its consequences are far reaching, as risk aversion also affects technology adoption, production and consumption decisions.

In particular the effects are more apparent when considering adoption of new technologies as an adaptation strategy for climate variability. Therefore, a model that incorporates agent-specific risk preferences into the decision of whether to adopt a

technology or not by considering heterogeneity among potential adopters will be vital not only to understand adoption patterns overtime, but also to design appropriate technology under climate variability. In the current model implementation, risk aversion is at least implicitly captured, as the model uses a parameterized version of consumption and production coefficients that reflect observed risk aversion behaviours. However, under climate variability these parameters might change as a result of climate variability effects on risk aversion. As such, the explicit representation of risk aversion in MPMAS could allow assessing climate impacts at household level even more precisely.

#### 6.5.3 Endogenous price formation

In the analysis of price variability, it is important to consider year-to-year price changes when considering the possibility of co-variation of price with climate variables. Price may change due to climate variability or due to other economic outcomes, such as changes in trade regimes, exchange rates, etc. While analyzing price variability effects as such, one has to identify climate induced price variability from non-climate induced variability. For example, when analyzing the impacts of price variability in Ethiopia and Ghana we considered both climate and non-climate induced price variability, which allowed us to capture the full welfare effects of productivity and market shocks. However, if the objective is to examine the effects of climate variability induced price changes on household welfare, one has to use an endogenous price formation model or estimate an econometric model on the effects of climate variables on the evolution of market prices for use as parameters in a simulation model. Extending the current study with endogenous price formation would be an important step for examining the effects of climate variability induced price changes on household welfare.

### 6.6 Policy implications

Our results on the effects of climate and price variability have many relevant policy implications. Even without the absolute magnitude of the effects, policy makers can use the results of this thesis to identify vulnerable groups to climate and price variability. Given that 'self'-coping strategies were not sufficient in shielding households against the impacts of climate and price variability, policy interventions designed to improve the asset-base of farm households will be very important. In addition, provision of other ex-post coping mechanisms will be important to avoid households engaging in coping mechanisms that erode their assets. These include, for example, coping through the sale of livestock, which might lead to long-term asset poverty traps. As such, considering the long-term implication of climate and price variability on a household's ability to recover from such shocks and poverty traps must be taken into consideration. In addition, well-targeted consumption credits, such as food for work and other production-oriented safety nets, will be important in reducing the impacts of variability while also improving productivity. In areas where agricultural productivity is very low or where production potentials are very limited, moving away from agriculture or diversification of livelihood is important.

Further, in addition to improving the coping ability of farm households, policy interventions designed at improving the ex-ante adaptive capacity of farm households will be very crucial. For the case of Ethiopia, our analysis on the effectiveness of adaptation options clearly showed that instead of a single course of action, strategies composed of a portfolio of actions (such as credit and fertilizer subsidies alongside new technologies) will be effective in reducing the impacts of climate and price variability. However, under circumstances where improved seed varieties are only available with unaffordable prices or without access to credit, such an intervention may fall short in achieving the intended results. As such, policy makers must create sound institutional capacities to insure that such interventions are accessible to poor farm households. Addressing market imperfections with regard to credit, fertilizer and the use of improved seed through effective targeting requires strengthening existing institutions. For example, creating an agricultural information system through mobile or radio technology in a manner that is understandable and useful for farmers would be a good policy intervention to reduce such information externalities. In Ghana, policy interventions aimed at improving the provision of short-term production credit along with the current irrigation facilities will be crucial. However, policy interventions through a single course of intervention, either through credit or irrigation alone, are likely to fail. The need for a mix of interventions is therefore important if the adverse effects of climate and price variability are to be reduced.

While designing adaptation options, a clear distinction should be made on what is needed in the short-run and what is needed in the long-run. Even though, short-run

interventions aimed at improving current vulnerability are important, improving productivity requires large investments and interventions in the form of packages. Since our simulation clearly showed intervention through complementary packages is the only effective mechanism to improve livelihood under variability, strengthening institutional capacity is very crucial. Given that both climate and price variability have an adverse effect, policy interventions that yield payoffs in the short-run are required. These include policy interventions to improve the use of available current technologies, including irrigation and improved seed. Improving the use of agricultural inputs such as fertilizer through credit and off-farm income generating opportunities will also be crucial. Providing subsidies without complementary packages will provide only marginal benefits. As a result, designing smart subsidies along with other complementary inputs will be crucial. Long-term interventions aimed at improving the adaptive capacity of farm households in the long-term are also necessary. These include the introduction of new crop varieties that are adapted to the local climate condition and the development and expansion of production through irrigation.

Focusing on targeting particular areas to improve productivity is also another area of intervention, as the impacts are quite heterogeneous across regions and households. Providing the necessary input packages in areas where the highest potential is expected instead of providing packages in a one size fits all approach is very crucial. In areas where land is degraded and productivity is low, interventions that improve land management practices will be important. For example, due to lack of economies of scale, adoption of technologies on a small fragmented land may not pay off or may not reach full potential. Not only targeting potential areas, but also targeting potential crops is also important. Traditional staple crops, such as teff in the case of Ethiopia, have low responses to input use. Improving the productivity of crops with high potential gains, such as maize and wheat, will also be an important area of intervention in the long-run.

There is a need for complimenting local social capital and links with extension services, as well as the need for scaling up local safety nets such as *Iddir*. As such, policy interventions should consider promoting formal credit access as well as scaling up the capacity of informal social networks by providing initial resources. The above assertion is supported for the following reasons: i) social capital enables farmers to

alleviate labour shortages through labour exchange arrangements; ii) it can be used as a source of finance for technology adoption in the absence of formal credit markets and iii) it allows information to flow, thereby reducing information asymmetry.

Our result further underscores the need for understanding the food security implications of price variability. As such, policy interventions geared towards improving output and input market access to farmers through prudent management of price variability will be very crucial. In addition, investment in crops with high relevance for food security would be important. We found that high price variability exacerbates food insecurity and therefore in the short-run policy makers must consider at price stabilization policies, such as reducing price margins to improve the earning capacity of farm households, increasing investment in scientific research on crop productivity improvement, developing infrastructure and reducing risk through crop index insurance mechanisms and grain reserves for unanticipated price changes..

Moreover, given that climate variability reduces the uptake of technology, due emphasis must be given to the management of down-side risk. For example, due to consumption requirements, households may produce crops with low mean and low variance, leading to poverty traps. Policy interventions that improve technology uptake must be designed along with consideration of the implication of such risks. These include provision of weather index-based crop and livestock insurance not based on objective measure of rainfall shocks but on the actual loses of farm households. The result of our simulation experiment and econometric analysis clearly indicates that risk management is crucial.

The result on the distributional aspect of climate and price variability also suggested the need for context-specific research. This result has a wider policy and research implication. Policy makers, NGOs and international organizations engaged in development activities need to consider best-fits instead of one size fits all intervention and researchers need to apply methods that capture farm and household level decision making and constraints.

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