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Dissertation

**Smallholder adaptation through agroforestry:
Agent-based simulation of climate and price
variability in Ethiopia**

submitted by

Habtamu Demilew Yismaw

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Dedicated to Asmare Demilew

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Examination Committee

Chair of Examination: Prof. Dr. Stefan Böttinger, University of Hohenheim

First Examiner: Prof. Dr. Thomas Berger, University of Hohenheim

Second Examiner: Prof. Alemu Mekonnen, Addis Ababa University

Third Examiner: Dr. Christian Troost, University of Hohenheim

Summary

Climate variability has been posing formidable policy challenges in Ethiopia by deteriorating rural livelihoods. Climate variability-induced shocks have a profound impact on smallholder farmers' welfare both in the short run via reducing production and increasing output prices and in the long run by depleting productive farm assets and leading them to a poverty trap. However, the impact of shocks on smallholders' welfare depends on their choice of adaptation and coping measures to deal with them, which are in turn farmer-specific. This thesis applied an integrated econometric analysis and farm-level simulations to assess smallholder farmers' adaptation and coping measures under extreme climate and price variability in Ethiopia. The thesis provides a special focus on the role of investment in small-scale agroforestry to curb the adverse effects of shocks.

Drought, hailstorms, pests, and crop diseases are identified as the most frequent and intense climate variability-induced shocks in Ethiopia. Smallholders' dominant adaptation and coping measures for each shock are identified using logistic principal component analysis (LPCA). The application of dimensionality reduction of binary data using LPCA to select smallholder farmers' dominant adaptation and coping measures is unique to this study. Results show that planting stress-resistant crops and varieties, early planting, increasing seed rate, and soil and water conservation practices are the dominant ex-ante adaptation measures. Whereas selling livestock, selling assets, reducing consumption, borrowing and replanting are the dominant ex-post coping measures.

In later sections, household-specific drivers of smallholder farmers' choice of adaptation and coping measures are disentangled using multivariate probit regression (MVP) for each shock. Gender, knowledge and experience, participation in rural institutions, social networks, resource endowments, and their shock experience and expectation are the significant drivers of farmers' choices of ex-ante adaptation and ex-post coping measures. Results suggest that smallholder farmers' choice of measures to deal with climate variability-induced shocks is highly distinctive and depends on their socioeconomic settings, experience and knowledge, and their interactions with the environment. Correlation analysis both in LPCA and MVP results show that most of the measures farmers choose are complementary, which implies that no single measure is robust and works best for all farmers. Farmers invest more on ex-post measures than ex-ante measures. Those who invest on tree perennials as ex-ante drought measures are less likely to use severe measures such as selling livestock and other assets in the aftershock.

The econometric analysis in the first part of the thesis establishes a descriptive analysis of smallholder farmers' behavioral responses to climate variability-induced covariate shocks. This captures the behavior of farmers in the status quo. However, it does

not tell us much about how farmers would behave in different future circumstances, especially with extreme climate and price variability. This requires a prescriptive and descriptive approach with a detailed investigation of farmers' behavior down to the plot level. To achieve this objective, the second part of the thesis applies household-level micro-simulation to analyze ex-ante planning and ex-post responses to future climate and price variability, focusing on the role of smallholder farmers' investment in woodlot perennials to their livelihoods. The agent-based simulation package - Mathematical Programming-based Multi-Agent Systems (MPMAS) is used for this purpose to capture investment, production, and consumption decisions at the farm household level. A farm decision model representing smallholder farmers in the Upper Nile Basin in Ethiopia is developed accordingly. The farmers in the area are known for their integrated crop-livestock system, and a unique *Acacia Dicurrens* based *taungya* system in the country. This thesis shows a first-time use of an agent-based modeling approach representing the acacia-based *taungya* system in the Upper Nile Basin in Ethiopia, which is another contribution of this study.

The farm decision model is validated using empirical data and interactive sessions with experts. Another methodological novelty of this study is developing and using interactive web applications to validate the farm decision model with experts remotely due to the COVID-19 pandemic. Interactive model validation is not new in agent-based modeling using MPMAS. However, the web-based R Shiny app and an integrated web-based expert survey questionnaire app is an original contribution of this study. The study also uses Zoom virtual conferencing to record all interactive validation sessions with experts.

Two simulation experiments were designed to quantify the effects of shocks and price variability on agents' livelihoods. The High-Performance Computing platform in Baden Wurttemberg (bwHPC) is used to run simulation experiments for this study. The first simulation experiment aims at measuring the effects of shocks on agents' livelihoods and the effectiveness of ex-ante planning to curb the adverse effects of these shocks. The application of model features on agents' ex-ante preparation for the possible occurrence of shocks within the farm decision model is a new development in this study. Accordingly, the frequent and intense crop and tree diseases in the area - potato late blight and acacia seedling disease are introduced as shocks in the model. Simulation results show that both potato late blight and acacia seedling disease reduce annual per capita discretionary income significantly and forcing some poor resource agents to fail to fulfill minimum non-food expenditure. The trade-off in agents' land-use decisions between trees and crops by agents shows that they prefer to plant trees than crops as an ex-ante planning strategy for shocks.

The second simulation experiment aims at examining the effect of long-run expected price changes, mainly on land-use decisions of agents in the model. Four future price scenarios are designed, and the results are compared with the baseline to examine the effect on agents' discretionary income and land-use decisions. The purpose of this simulation experiment is to see if there is a deviance from croplands to woodlots and vice versa based on long-run changes in expected prices. Simulation results show that

agents are highly responsive to changes in expected prices in the long run, except for the expected price of bamboo. In cases where there is a decrease in the expected price of acacia charcoal or an increase in the expected price of crops or both, results show that agents will go back to potatoes and wheat-dominated production systems instead of the acacia-dominated production system .

This study suggests that supporting farmer adaptation to climate variability-induced shocks should focus on policy interventions related to crop and land management activities. Policy interventions should also focus on building the household asset base to boost farmers' coping ability and resilience to shocks. Moreover, results suggest that robust climate adaptation and mitigation interventions should take the heterogeneity of farmers into account. Furthermore, both econometrics and farm-level simulation analyses show the importance of planting trees as a crucial adaptation strategy. Findings suggest that investment in woodlot perennials is an essential adaptation strategy for smallholder farmers with scarce resource settings and should be promoted and scaled to a broader area in the region.

Zusammenfassung

Klimavariabilität hat Äthiopien vor gewaltige politische Herausforderungen gestellt, indem sich die Lebensgrundlagen auf dem Land wesentlich verschlechterten. Durch Klimavariabilität verursachte Schocks haben einen tiefgreifenden Einfluss auf das Wohlergehen von kleinbäuerlichen Betriebs-Haushalten, sowohl kurzfristig durch die Verringerung der Produktion und den Anstieg der Erzeugerpreise als auch langfristig durch die Erschöpfung der produktiven landwirtschaftlichen Vermögenswerte und das Abgleiten in eine Armutsfalle. Die Auswirkungen von Schocks auf die Wohlfahrt von kleinbäuerlichen Betriebs-Haushalten hängen jedoch von der Wahl der Anpassungsmaßnahmen ab, die wiederum haushaltsspezifisch sind. Diese Arbeit wendet integrierte ökonometrische Analysen und Simulationen auf Haushaltsebene an, um die Anpassungsmaßnahmen von Kleinbauern unter extremen Klima- und Preisschwankungen in Äthiopien zu bewerten. Die Arbeit legt einen besonderen Fokus auf die Rolle von Investitionen in kleinbäuerliche Agroforstwirtschaft, um die negativen Auswirkungen von Schocks zu dämpfen.

Dürre, Hagelstürme, Schädlinge und Pflanzenkrankheiten werden als die häufigsten und intensivsten Schocks identifiziert, die durch Klimavariabilität in Äthiopien verursacht werden. Die wichtigsten Anpassungsmaßnahmen der kleinbäuerlichen Betriebs-Haushalte für diese Schocks werden mit Hilfe der logistischen Hauptkomponentenanalyse (LPCA) identifiziert. Die Anwendung der Dimensionalitätsreduktion von binären Daten mittels LPCA zur Auswahl der dominanten Anpassungsmaßnahmen der Kleinbauern ist einzigartig in dieser Studie. Die Ergebnisse zeigen, dass der Anbau von stressresistenten Pflanzen und Sorten, die frühe Aussaat, die Erhöhung der Saatgutmenge und boden- und wasserkonservierende Praktiken die dominanten ex-ante Anpassungsmaßnahmen sind. Die dominierenden ex-post Maßnahmen sind der Verkauf von Vieh, der Verkauf von Vermögenswerten, die Reduzierung des Konsums, die Aufnahme von Krediten und die Neubepflanzung.

Im Folgenden werden die haushaltsspezifischen Einflussfaktoren auf die Wahl der Anpassungsmaßnahmen der Kleinbauern mithilfe einer multivariaten Probit-Regression (MVP) für jeden Schock aufgeschlüsselt. Geschlecht, Wissen und Erfahrung, Beteiligung an ländlichen Institutionen, soziale Netzwerke, Ressourcenausstattung sowie die Schockerfahrung und -erwartung sind die signifikanten Einflussfaktoren für die Wahl von ex-ante und ex-post Maßnahmen. Die Ergebnisse deuten darauf hin, dass die Wahl der Maßnahmen zur Bewältigung von durch Klimavariabilität verursachten Schocks bei Kleinbauern sehr unterschiedlich ausfällt und von ihrem sozioökonomischen Umfeld, ihrer Erfahrung und ihrem Wissen sowie von ihren Interaktionen mit der Umwelt abhängt. Korrelationsanalysen sowohl in der LPCA als auch in den MVP-Ergebnissen zeigen, dass die meisten von den Landwirten gewählten Maßnahmen komplementär sind, was bedeutet, dass keine einzelne Maßnahme robust ist und gleichermaßen bei allen Landwirte wirkt. Die Landwirte investieren mehr in

ex-post-Maßnahmen als in ex-ante-Maßnahmen. Diejenigen, die in die Anpflanzung von Bäumen als ex-ante Maßnahmen investieren, nutzen weniger schwerwiegende Maßnahmen wie den Verkauf von Vieh und anderen Vermögenswerten.

Die ökonometrische Analyse im ersten Teil der Arbeit liefert deskriptive Statistiken der Verhaltensreaktionen von kleinbäuerlichen Betriebs-Haushalten in Bezug auf klimavariabilitätsinduzierte, kovariate Schocks. Dies erfasst das Verhalten der Haushalte im Status quo. Die Analyse sagt jedoch nicht viel darüber aus, wie sich die kleinbäuerlichen Betriebs-Haushalte unter anderen zukünftigen Umständen verhalten würden, insbesondere bei extremer Klima- und Preisvariabilität. Dies erfordert einen präskriptiven und deskriptiven Modellansatz mit einer detaillierten Untersuchung des Verhaltens der Landwirte bis hinunter auf die Parzellenebene. Um dieses Ziel zu erreichen, wendet der zweite Teil der Arbeit eine Mikrosimulation auf Haushaltsebene an, um die ex-ante Planung und die ex-post Reaktionen auf zukünftige Klima- und Preisschwankungen zu analysieren, wobei der Schwerpunkt auf der Rolle der Investitionen in Agroforstsysteme liegt. Das agentenbasierte Simulationspaket MPMAS wird zu diesem Zweck verwendet, um Investitions-, Produktions- und Verbrauchsentscheidungen auf der Ebene der landwirtschaftlichen Haushalte zu erfassen. Ein landwirtschaftliches Entscheidungsmodell, das Kleinbauern im oberen Nilbecken in Äthiopien repräsentiert, wird entsprechend entwickelt. Die Landwirtschaft in diesem Gebiet ist bekannt für ihr integriertes Ackerbau-Viehzucht-System und ein im Land einzigartiges, auf Acacia Dicurrens basierendes Taungya-System. Diese Arbeit zeigt den erstmaligen Einsatz eines agentenbasierten Modellierungsansatzes, der das Taungya-System im oberen Nilbecken in Äthiopien darstellt, was ein weiterer Beitrag dieser Studie ist.

Das landwirtschaftliche Entscheidungsmodell wird anhand empirischer Daten und interaktiver Modellierungs-Sessions mit Experten validiert. Eine weitere methodische Neuheit dieser Studie ist die Entwicklung und Verwendung interaktiver Webanwendungen zur Online-Validierung des landwirtschaftlichen Entscheidungsmodells mit Experten aufgrund der COVID-19-Pandemie. Die interaktive Modellvalidierung ist bei der agentenbasierten Modellierung mit MPMAS nicht neu. Die webbasierte R Shiny-App und eine integrierte webbasierte App zur Expertenbefragung ist jedoch ein originärer Beitrag dieser Studie. Die Studie verwendet auch virtuelle Zoom-Konferenzen, um alle interaktiven Validierungs-Sessions mit Experten aufzuzeichnen.

Zwei Simulationsexperimente wurden entworfen, um die Auswirkungen von Schocks und Preisschwankungen auf den Lebensunterhalt der Modellagenten zu quantifizieren. Die High-Performance Computing Plattform in Baden Württemberg (bwHPC) wird genutzt, um Simulationsexperimente für diese Studie durchzuführen. Das erste Simulationsexperiment zielt darauf ab, die Auswirkungen von Schocks auf den Lebensunterhalt der Modellagenten und die Effektivität der Ex-ante-Planung zur Eindämmung der negativen Auswirkungen dieser Schocks zu messen. Die Anwendung von Modellmerkmalen zur Ex-ante-Vorbereitung der Agenten auf das mögliche Auftreten von Schocks innerhalb des landwirtschaftlichen Entscheidungsmodells

ist eine neue Entwicklung in dieser Studie. Dementsprechend werden die häufig auftretenden Pflanzen- und Baumkrankheiten in der Region - die Kraut- und Knollenfäule der Kartoffel und die Akazienkrankheit - als Schocks in das Simulationsmodell eingeführt. Die Simulationsergebnisse zeigen, dass sowohl die Kraut- und Knollenfäule als auch die Akazienkrankheit das jährliche frei verfügbare Pro-Kopf-Einkommen signifikant reduzieren und bei einigen armen Agenten-Haushalte auch die Mindestnahrungsverfügbarkeit nicht mehr sichergestellt ist. Der Trade-off in den Landnutzungsentscheidungen der Agenten zwischen Bäumen und Feldfrüchten zeigt, dass sie als Ex-ante-Planungsstrategie für Schocks lieber Bäume als Feldfrüchte pflanzen.

Das zweite Simulationsexperiment zielt darauf ab, den Effekt von langfristig erwarteten Preisänderungen zu untersuchen, hauptsächlich auf Landnutzungsentscheidungen der Agenten im Modell. Es werden vier zukünftige Preisszenarien entworfen, um die Auswirkungen auf das tatsächlich frei verfügbare Einkommen der Agenten und die Landnutzungsentscheidungen zu untersuchen. Der Zweck dieses Simulationsexperiments ist es, zu sehen, ob es eine Umwandlung von Ackerland zu Baumflächen und umgekehrt gibt, basierend auf langfristigen Änderungen der erwarteten Preise. Die Simulationsergebnisse zeigen, dass die Agenten langfristig stark auf Änderungen der erwarteten Preise reagieren, mit Ausnahme des erwarteten Preises für Bambus. In den Fällen, in denen der erwartete Preis für Akazienholzkohle sinkt oder der erwartete Preis für Feldfrüchte steigt oder beides, zeigen die Ergebnisse, dass die Agenten zu den von Kartoffeln und Weizen dominierten Produktionssystemen zurückkehren, anstatt zu dem von Akazien dominierten Produktionssystem.

Diese Studie legt nahe, dass sich die Unterstützung der Anpassung der Landwirte an durch Klimavariabilität verursachte Schocks auf politische Interventionen konzentrieren sollte, die sich auf Anbau- und Landmanagementaktivitäten beziehen. Politische Interventionen sollten sich auch auf den Aufbau der Vermögensbasis der Haushalte konzentrieren, um die Anpassungsfähigkeit und Widerstandsfähigkeit der Bauern gegenüber Schocks zu stärken. Darüber hinaus legen die Ergebnisse nahe, dass robuste Maßnahmen zur Klimaanpassung und -minderung die Heterogenität der Landwirte berücksichtigen sollten. Darüber hinaus zeigen sowohl ökonometrische als auch Simulationsanalysen auf Betriebsebene die Bedeutung des Anpflanzens von Bäumen als eine entscheidende Anpassungsstrategie. Die Ergebnisse deuten darauf hin, dass Investitionen in Agroforstsystemen eine wesentliche Anpassungsstrategie für Kleinbauern mit knappen Ressourcen sind, entsprechend gefördert und auf ein größeres Gebiet in der Region ausgeweitet werden sollten.

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List of acronyms

AD Acacia Dicurrens

AEZ Agro-ecological Zone

ARARI Amhara Regional Agricultural Research Institute

ARC Agricultural Research Center

CIMMYT International Maize and Wheat Improvement Center

COVID-19 Corona virus disease (2019)

CRGE Climate Resilient Green Economy strategy of Ethiopia

CSA Central Statistical Agency of Ethiopia

EIAR Ethiopian Institute of Agricultural Research

ETB Ethiopian Birr

FAO Food and Agricultural Organization of the United Nations

FGDs Focus Group Discussions

KIIs Key Informant Interviews

LGP Length of Growing Period

LPCA Logistic Principal Component Analysis

LSVD Logistic Singular Value Decomposition

MAS Multi-agent Systems

MIP Mixed Integer Programming

MPMAS Mathematical Programming Based Multi-Agent Systems

MPMASQL4 Mathematical Programming Based Multi-Agent Systems Query
Language version 4

MVP Multivariate Probit Regression

NPV Net present value

ODD Overview, Design concept and Details

PCA Principal Component Analysis

SDGs Sustainable Development Goals

SIMLESA Sustainable Intensification of Maize and Legume Cropping Systems for Eastern and Southern Africa

SNNP Southern Nations, Nationalities and Peoples of Ethiopia

SOBOL Variance-based sensitivity analysis

TLU Tropical Livestock Unit

UI User Interface

UNDP United Nations Development Programme

USD United States Dollar

WHMFS Western Highland Maize Mixed Farming System

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Chapter 1

Introduction

Chapter objectives

- *Establishing stylized facts on adaptation and mitigation of climate variability in scarce resource settings in general and in Ethiopia in particular*
 - *Explaining motivation and showing research gap which necessitates undertaking of this research*
 - *Setting objectives and corresponding research questions of the research*
 - *Explaining organization of the thesis*
-

1.1 Adaptation and Mitigation of Climate Variability in Scarce Resource Settings

Stylized facts in Ethiopian Context

Stylized fact 1: Agriculture is highly climate sensitive in Ethiopia

Agriculture in Ethiopia is predominantly rainfed and highly climate-sensitive. Though there are several rainfall regimes in the country, the Meher or Kiremt season (June - September) is the country's main rainy season, which accounts for 50 to 80 % of the total annual rainfall (Asfaw et al. 2018) and (CRGE 2019). Historically, droughts and other climate variability induced shocks in the country are associated with the failure of this main rainy season (Segele and Lamb 2005). Attributed to the global south-north movement and inter-topical convergence zone, rainfall in Ethiopia is characterized by high spatial variations (Korecha and Barnston 2007). The variability of rainfall is higher in the rift valley and eastern part than the country's highlands and western part. The inter annual variability of rainfall in Ethiopia is affected negatively by El Nino (Schreck and Semazzi 2004) and positively by La Nina (Schreck and Semazzi 2004; Segele, Lamb,

and Leslie 2009). The total annual rainfall in the country has been declining on average since 1950 (Jury and Funk 2013). Future rainfall projections based on historical data show a slight increase in annual rainfall (Jury and Funk 2013; Kassie et al. 2014) but higher variability until the end of the 21st century (CRGE 2019).

Because of its tropical latitude, Ethiopia has a mild temperature. Like average annual rainfall, the annual average temperature has large spatial differences based on altitude, with 15 to 20 °C in highlands to 25 to 30 °C lowlands (CRGE 2019). Inter annual temperature variations have been recording an increasing trend since the 1950s with regional variations (Jury and Funk 2013). Projections of mean annual temperature show a consistent warming trend in the last decades (Kassie et al. 2014).

Stylized fact 2: Climate variability has a profound impact on smallholder livelihoods in Ethiopia

Ethiopian agriculture is dominated by subsistence smallholder farmers characterized by high poverty status and food insecurity (Berck, Berck, and Di Falco 2018). Climate variability and the subsequent drought, price shocks, and food insecurity have posed formidable policy challenges in Ethiopia for several decades. Climate variability-induced shocks profoundly impact the economy by reducing agricultural production, inflating agricultural output prices (Hill and Porter 2017) and deteriorating smallholder farm household welfare (Yalew et al. 2018). The effect of climate variability-induced shocks on smallholders' livelihoods is multi-faceted. The indirect effects of drought on household welfare via its impact on increasing food prices and reducing livestock prices (due to relatively lower supply attributed to drought), for instance, are often greater, particularly for net buyers, than its direct effect on agricultural production (Holden and Shiferaw 2004; Menghistu, Mersha, and Abraha 2018).

Erratic rainfall and increasing inter-annual temperature variability have caused several climate variability induced shocks in Ethiopia for several decades. Recurrent climate variability induced droughts, floods, hailstorms, pests, and crop diseases have been threatening the lives of tens of millions in Ethiopia that are a cause of several hundreds of thousands. Mulugeta, Tolossa, and Abebe (2017) indicated that erratic rainfall and high temperature-induced droughts severely affect farmers in Ethiopia's southern and eastern regions. According to the CRGE (2019), drought in 2003 and 2015 put 12 and 10 million Ethiopians in urgent need of humanitarian assistance and the drought in 1983 took the lives of more than 300,000 Ethiopians.

For the past half a century, climate variability induced shocks have placed millions of poor rural smallholder households and pastoralists in the position of acute water and food shortage and made them vulnerable to the outbreak of diseases (Enbiale and Ayalew 2018; FAO 2016). Since 1965, Ethiopia has experienced 15 drought years with an average of one in four years (Richman, Leslie, and Segele 2016). In 2015, for example, the two main rainy seasons (meher and belg) failed due to El Nino, which left 10.2 million people (10% of the total population) in urgent need of humanitarian food assistance and 6 million children at risk from hunger, disease and lack of water (FAO 2016; HRD 2016). Besides, livelihoods were affected due to poor health and livestock

death or remained hazardous because of limited access to seeds and other agricultural inputs for the following production year.

In addition to drought and price shocks, smallholders' livelihoods in Ethiopia are also threatened by frequent pests, crop disease and hailstorms (Abate, van Huis, and Ampofo 2000; Kebede et al. 2019; Kumela et al. 2019). Sometimes the intensity of these shocks is more devastating than successive droughts (Zheng and Byg 2014). Climate variability has a significant effect on pest and crop disease occurrences through altering rainfall and precipitation (Del Rio 2014). Pests and crop diseases have been severe threats for smallholders in Ethiopia, reducing agricultural production as far as 35% in bad years (Erenstein et al. 2019). In 2017, for example, an invasion of Fall Army Worm (*Spodoptera frugiperda*) caused estimated average crop damage of 32% in the production of maize in the country (0.8 to 1-ton reduction per ha) (Kumela et al. 2019). Hailstorms cause substantial production losses, sometimes reaching up to 100% (Amare and Simane 2017). Coupled with the absence of weather-indexed insurance in most parts of the country, such losses make farmers sell their key assets such as livestock to cope up with the shocks or rely on aid and safety nets otherwise (Peterson 2012).

Climate variability-induced shocks cause hunger and income deprivation when they occur and lead to a loss of assets (livestock, savings, soil fertility, human capital) that hamper the productivity and income opportunities of the farmer in the long run. Also, the risk of their occurrence alone may require farmers to reserve part of their resources to prepare for adverse outcomes (ex-ante adaptation) – given a lack of access to fully functioning credit and insurance markets (Cooper et al. 2008 ; Hertel, Burke, and Lobell 2010). The necessity to ensure food security in bad years puts resource-poor smallholders in a more disadvantaged position than more resource-rich farms, who can pursue more profitable but riskier production options (Dercon and Christiaensen 2011). Climate variability may, in this way, lock smallholders within a poverty trap that will transmit over generations, given that the starting position of a new household is determined to a large part by intergenerational transfers of productive assets and human capital (Kumar and Quisumbing 2012).

Stylized fact 3: Climate variability has a profound impact on all pillars of food security

Climate variability-induced shocks profoundly impact food security in developing countries by altering availability, access, and utilization of food and destabilizing food systems (Mbow et al. 2014 ; Ringler 2010). Climate variability diminishes the availability of food by reducing crop productivity (Wheeler and Braun 2013). Currently, crop production in developing countries is characterized by inefficiency in production and a wider potential yield gap that could be closed without introducing new and innovative technologies (Henderson et al. 2016). Climate variability exacerbates the problem by worsening the prevailing inefficiency in crop production and widens the yield gap further (Mbow et al. 2014). Mueller et al. (2012) showed that alongside fertilizer use and irrigation, climate variability significantly impacts global yield variability.

Intra and inter-seasonal variations in temperature and precipitation have a significant impact on food availability by reducing staple cereal crops' productivity in Eastern Africa (Adhikari, Nejadhashemi, and Woznicki 2015). Simulated crop yield results in future climate conditions show up to a 10% decrease in maize production in Africa and Latin America by 2055 (Jones and Thornton 2003). A study in Tanzania shows that the prevalence of extreme events significantly reduces simulated yields of maize, sorghum, and rice by 2050 (Rowhani et al. 2011). Similarly, sorghum yield substantially declines with future climate variability in Ethiopia, which in turn reduces the availability of food for smallholders (Eggen et al. 2019). Furthermore, climate variability diminishes the availability of food by reducing livestock productivity (Mbow et al. 2014 ; Rojas et al. 2017). Megersa et al. (2014) showed that seasonal change of rainfall and temperature is significantly associated with reduced cattle size due to a high mortality rate.

Besides reducing food availability, climate variability worsens smallholders' food security by restricting their access to food by reducing agricultural production and deteriorating purchasing power via price and income effects (Mbow et al. 2014 ; Wheeler and Braun 2013). Reduced agricultural production limits the amount of food available in the household and diminishes their total farm income (Wossen et al. 2018). The limited supply of agricultural output, on the other hand, increases the market prices of food items (Chen and Villoria 2019). The combined effect of income and prices cripples smallholders' purchasing power to fulfill their minimum food requirements (Wheeler and Braun 2013). The effect is severe for smallholders with relatively lower resource settings (Carter et al. 2007) and limited adaptive capacity (Mbow et al. 2019). Furthermore, the effect is more disastrous for women and children as they are more resource-constrained (Mbow et al. 2019).

By altering food quality and food safety, climate variability has a direct and indirect impact on smallholders' utilization of food (Mbow et al. 2019 ; Wheeler and Braun 2013). Climate variability impairs smallholders' access to an adequate diet, sanitation and health care and thus, their nutritional status creates inadequate access to clean drinking water (Wheeler and Braun 2013). Climate variability induced toxins and microorganisms' prevalence deters food safety and results in food losses (Ayelign and Saeger 2020 ; Mbow et al. 2019). Ayelign and Saeger (2020) identified adverse effects of Mycotoxin on food safety and a significant loss of income to smallholders in Ethiopia as a result. Besides, the nutritional quality of food is affected by climate variability through its direct impact on plants and animals' biological processes and reduced growth and yields due to increases in CO₂ concentration (Mbow et al. 2019). Furthermore, the recurrence and severity of climate variability induced extreme events put the food system at risk due to short term variability in the food supply through disrupting food prices and agricultural income (Wheeler and Braun 2013). This, in turn, puts smallholders to be dependent on food aid and humanitarian assistance.

Stylized fact 4: there is a greater need for practical adaptation and mitigation strategies to enhance food security under climate variability

Weathering the adverse effects of climate variability and enhancing food security among smallholders demands a greater need for sound adaptation and mitigation strategies (Berck, Berck, and Di Falco 2018). Farmers employ a series of adaptation and mitigation strategies to reduce the impact of extreme climatic events ranging from crop management activities such as adjusting cropping calendar, applying improved technologies and inputs and crop diversification to land-based adaptation practices and seasonal migration (Bedeke et al. 2019). There is a wealth of empirical evidence on potential and effective adaptation and coping strategies to ensure smallholders' food security under climate variability.

It has been shown that the availability of food under climate variability improves significantly via closing crop yield and productivity gaps through the application of new and improved technologies. Challinor et al. (2014) showed an average simulated yield increase of 7 to 15% for main crops such as maize, wheat and rice under climate change due to crop level adaptation practices. Application of improved maize varieties coupled with improved crop and agronomic practices increase maize yield and enhance adaptation to climate change (Shiferaw et al. 2011). The effectiveness of improved maize and wheat varieties is even higher when it is accompanied by access to short term credit (Wossen et al. 2018) and fertilizer subsidy (Berger et al. 2017).

Better food storage provides a sustained food availability and helps farmers as a coping strategy to smooth food consumption in the aftershock of climate variability induced shocks (Sunano 2020). Enhancing integrated adaptation practices and risk management, including marketing mechanisms and crop and livestock insurance, increases food system stability (Mbow et al. 2019). Crop diversification enhances smallholders' access to food under climate variability by increasing farm income and labor availability for off-farm work (Asmare, Teklewold, and Mekonnen 2019). Food availability and dietary intake of meat and milk products are potentially improved by diversifying livestock production in the presence of climate variability (Megersa et al. 2014). The impact of climate variability on smallholders' access and utilization of food can also be mitigated by increasing supply chains' efficiency, reducing food waste, and access to storage facilities (Mbow et al. 2019).

Stylized fact 5: Smallholders vulnerability to climate variability depends on agroecology and adaptive capacity

Smallholder exposure, adaptive capacity, and vulnerability to climate variability induced shocks in Ethiopia vary across agroecological systems (Tessema and Simane 2019). Similar variations were observed by Abeje et al. (2019). Ringler (2010) pointed out that inadequate and lack of access to credit, markets, information, risk-sharing tools, and property rights have limited smallholders' adaptive capacity to circumvent the negative impacts of climate change in Africa. Moreover, in another study, Lewis (2017) pointed out that the impact of climate variability on food security is different in different Ethiopia regions – the impact is higher in most marginal livelihood systems

and drier areas. Likewise, after showing the significant contribution of the adoption of climate-smart agricultural practices to nutrition security, Teklewold, Gebrehiwot, and Bezabih (2019) pointed out that such strategies' impact is different for different households based on resource availability between male and female farmers. This indicates that adaptation and coping of climate variability induced shocks should be tailored based on agroecology and socioeconomic status of smallholders Jones and Thornton (2003).

1.2 Motivation

Climate variability have been posing formidable policy challenges in Ethiopia for several decades. Climate variability induced shocks caused serious problems to smallholder farmers' welfare in Ethiopia both in the short run via reducing production and increasing output prices and in the long run by depleting productive farm assets and leading to the poverty trap. However, the impact of these shocks on farmers' welfare depends on the strategies farmers use to deal with them before and after their occurrence and is, therefore, farmer specific.

While climate variability is a global phenomenon for everyone within a given agroecological zone, impacts of climate variability can be very diverse, due to a strong heterogeneity in the resource base, socio-cultural ties, market and information access, and human capital of smallholder farmers (Berhanu and Beyene 2015; Caeyers and Dercon 2012; Wossen et al. 2018). As a result, adaptation and coping strategies that farmers are able and willing to select in response to climate variability induced shocks are specific to each farmer. Likewise, the success and robustness of these strategies depend not only on the frequency and extent of shocks but also, among other things, on their endowments, social networks, political affiliation and other community-level characteristics (Amare and Simane 2017; Caeyers and Dercon 2012; Wossen et al. 2018).

Berger et al. (2017) showed that household-specific characteristics in Ethiopia significantly determine farmers' choices of adaptation strategies. Similarly, a study in Zambia indicates that the adoption of conservation farming practices to deal with climate variability is determined by agroecological farmers' and socioeconomic factors (Arslan et al. 2014). Application of water and soil conservation practices, drought-tolerant varieties and chemical fertilizer depends on age and gender of household head, confidence on extension services and membership, on local organizations (Sisay and Kindu 2019). Application of climate-smart technologies in eastern Africa is derived by gender, perception of risk severity, technology awareness and access to input markets (Murage et al. 2015). Gebrehiwot and van der Veen (2013) examined household-specific determinants of the choice of adaptation strategies by smallholders and found education and age of household head, access to credit and agricultural services, wealth, knowledge on climate and temperature, as major factors exposure and experience to climate shocks and access to climate information increase farmers' chance of crop and livestock diversification to tackle the adverse effects of

climate variability and enhance food security (Mulwa and Visser 2020).

Farmers' adaptation to climate variability induced shocks also requires adopting more than one strategy for a risk factor (Khan et al. 2020). Attributed to their unobserved characteristics, smallholder decisions on choice of ex-ante and ex-post strategies are interrelated and interdependent to one another (Abay et al. 2018). Some of the strategies are conditional on the adoption of other strategies. In contrast, some strategies compete over the same resources. For example, on the one hand, farmers can choose either to sell tree perennials or to sell livestock as a coping strategy to escape the adverse effects of drought on their livelihoods. On the other hand, they may engage in off-farm activities instead of reducing consumption as a strategy to cope with a hailstorm. For smallholders, understanding which strategies compete over the same resource means saving important resources. However, the adoption of multiple strategies depends on household characteristics and differs from farmer to farmer (Tongruksawattana and Wainaina 2019).

In connection with this, scientific assessments intended to support the design of successful and robust climate adaptation policies should take the heterogeneity of farming households into account and assess the complementary and competitive combination of various ex-ante and ex-post coping strategies. Failure to consider the heterogeneity of farmers' adoption decisions in policy interventions results in unequal treatment of farmers and may even lead to maladaptation in a significant number of cases (Berger et al. 2017). The first part of this study integrates logistic principal component analysis and Multivariate probit regression to identify dominant strategies and disentangle farmer specific determinants of the choice of ex-ante and ex-post strategies for most frequent and intense climate variability induced shocks in Ethiopia. Further, the study signals robust strategy mixes by identifying complementary and competitive strategies for climate variability induced shocks.

In the second part of this study the emphasis is on agroforestry as a key instrument for adaptation and coping strategies for smallholders. The focus is on tree perennials – mainly *Acacia Decurrens* and *Bamboo* - most common among smallholders in North Western Ethiopian highlands. The multidimensional benefits of adopting agroforestry to rural livelihoods have recently got due attention worldwide (Sisay and Kindu 2019). For instance, it is explicitly stated in the UN Sustainable Development Goals (SDGs) that encourages the adoption of agroforestry in rural areas is identified as an important instrument to ensure food security (UNDP 2015). Besides, the adoption of agroforestry to the mainstream agricultural practices of crop and livestock production in Sub-Saharan Africa is recommended by major international organizations such as the Food and Agricultural Organization of the United Nations (FAO) food security of smallholder farmers. FAO also suggested governments in Sub Saharan Africa to incorporate agroforestry as a major strategy in their agricultural policies (Partey et al. 2017).

Agroforestry has an immense potential to effectively adapt and mitigate the impact of climate variability induced shocks on smallholder livelihoods through increasing farm income and restoring the environment (Bedeke et al. 2019)). There is well-established

empirical evidence on agroforestry’s role as an effective instrument to climate change coping and adaptation endeavors by smallholders. Linger (2014) showed that home garden forestry significantly improves smallholders’ income and serves as an effective strategy to mitigate the impact of climate variability. Similarly, smallholder agroforestry improves farmers’ living standards under climate variability in Ethiopia and Kenya through income generation and restoration of degraded land (Thorlakson and Neufeldt 2012).

Historically, inadequate land management practices coupled with long-lasting monoculture practice has led the soil in Ethiopian highlands to massive degradation through erosion and nutrient depletion. This soil degradation combined with high population growth in the rural areas engender deforestation and force agriculture into marginal lands and steep slopes. Moreover, there is an increased argument recently that agroforestry - as the major land-based mitigation strategy for climate variability - threatens food security by reducing food availability for smallholders (Mbow et al. 2019). High returns on investment from agroforestry drive smallholders to shift from crop management and social capital related adaptation strategies to land-based adaptation strategies to deal with climate variability. This reduces the amount of fertile land available for crop production and displaces crops to the less productive and high climatic risk and vulnerable areas (Mbow et al. 2019). Despite its contribution to farm income, however, there is a trade-off between food security and land-based adaptation strategies via reducing agricultural land (Doelman et al. 2020).

Following the success of *Eucalyptus Globulus* as a multi-purpose exotic perennial in the country, *Acacia Decurrens* was introduced to the Ethiopian highlands in the early 1990s for short-rotation forestry as part of the government’s plan not only to meet the increasing demand for firewood in the urban areas but also to reduce deforestation and increase soil fertility in rural areas. And thereby help smallholders’ smooth consumption, improve food security and reduce poverty, especially at extreme weather events. Currently, attracted by its dual benefit, smallholders in Ethiopian highlands are rapidly converting their croplands to *Acacia* woodlots and making a significant portion of their livelihood from it. With such a higher rate of land-use conversion understanding the effect of investment in woodlots on livelihoods in current and future climate and price variability is imperative.

In this respect, this research applies household level microsimulations to analyze the role of smallholders’ investment in woodlot perennials to livelihoods in the presence of climate and price variability. The agent-based simulation package Mathematical Programming-based Multi-Agent Systems (MPMAS) is used to capture production consumption and investment decisions at the farm household level. A recursive dynamic intertemporal planning model is developed using plot-level data collected from farm households in Ethiopian highlands in 2018 to capture farmers’ multiperiod investment in woodlot perennials alongside their annual non-separable production and consumption decisions (Berger et al. 2017). This enables us to show how climate and price variability changes farmers’ land-use and consumption decisions and thus effects their livelihoods.

1.3 Objectives and research questions

This study's overall objective is to assess farmers' behavioral choices of ex-ante adaptation and ex-post coping measures to climate variability- induced shocks in Ethiopia and examine the role of agroforestry as a cross cutting issue. The specific objectives are:

- Learn farmers' behavior in ex-ante and ex-post strategy choices and understand who chooses which strategy and examine if it is different across different households.
- Model farmers' behavior to deal with climate variability induced shocks to analyze potential improvements and optimal responses in robust strategy choices and the role of planting trees to it.
- Explore the potential of small-scale agroforestry (through investment in woodlot perennials) to livelihoods in the presence of climate and price variability.

The corresponding research questions are:

- What are household-specific drivers of farmers' choice of adaptation and coping measures to climate variability induced shocks?
- How far can planting trees (Acacia Decurrens and Bamboo) and the resultant surplus labor help farmers withdraw from vulnerability to climate variability?
- What is the effect of investment in woodlots on livelihoods in current and future climate and price variability?

1.4 Organization of the thesis

The thesis is organized into seven chapters. The second chapter presents data sources, study area and farming system and elicits the materials and methods used for analysis in the thesis. Both econometric and agent-based modeling methods used for data analysis in the thesis are described in this chapter. Chapter three to chapter five presents the results of the thesis. Chapter three presents econometrics results on farmers' choices of ex-ante and ex-post measures. Chapter four and five show validation results and simulation experiment results, respectively of the farm decision model. Discussion of the thesis's main findings are presented in the six chapter, and the seventh chapter elicits concluding remarks and way forward. Model documentation and other results of the thesis are presented in the Appendix A to C.

Chapter 2

Data and Methods

Chapter objectives

- *Describing study area and data sources*
 - *Introducing farming system the farm decision model in this thesis is built for*
 - *Describing methods of data analysis used in the thesis*
-

2.1 Data and study area

This study uses two data sets from two different sampling areas. The first sample encompasses smallholder farm households in the central rift valley, central and northwestern regions of Ethiopia. The data was collected in 2011 by the International Maize and Wheat Improvement Centre (CIMMYT) in collaboration with the Ethiopian Institute of Agricultural Research (EIAR) as part of the project entitled Sustainable Intensification of Maize and Legume Cropping Systems for Eastern and Southern Africa (SIMLESA). The sample covers major maize growing areas both in high and low rainfall receiving agro-ecologies. Since the project aimed at maize-based systems, nine sample districts located in three Regional States and eight administrative zones were selected based on maize production potential, environmental diversity, and geographical dispersion. These districts are Pawe from Benshangul Gumuz region; Meskan, Hawasa Zuria and Misrak Badawacho from SNNP region and Shalla, Gubeseyo, Dugda, Adami Tulu, and Bako Tibe are in Oromia region. From these districts a total of 898 households were randomly selected and interviewed (Chilot, Adam, and Menale 2017). Figure 2.1 shows the location of the sample districts.

Using this data, this study aims at establishing the dominant climate variability mitigation and adaptation measures of smallholder farm households in Ethiopia to the most frequent and intense risk factors they encounter. The dataset covers a wealth of information on the frequency and occurrence of a wide range of climate variability

induced shocks and the corresponding ex-ante and ex-post strategy choices of farm households in the area, among other things. The vast sampling area provides a platform to undertake a countrywide analysis of effect, adaptation, and mitigation of climate variability induced shocks.

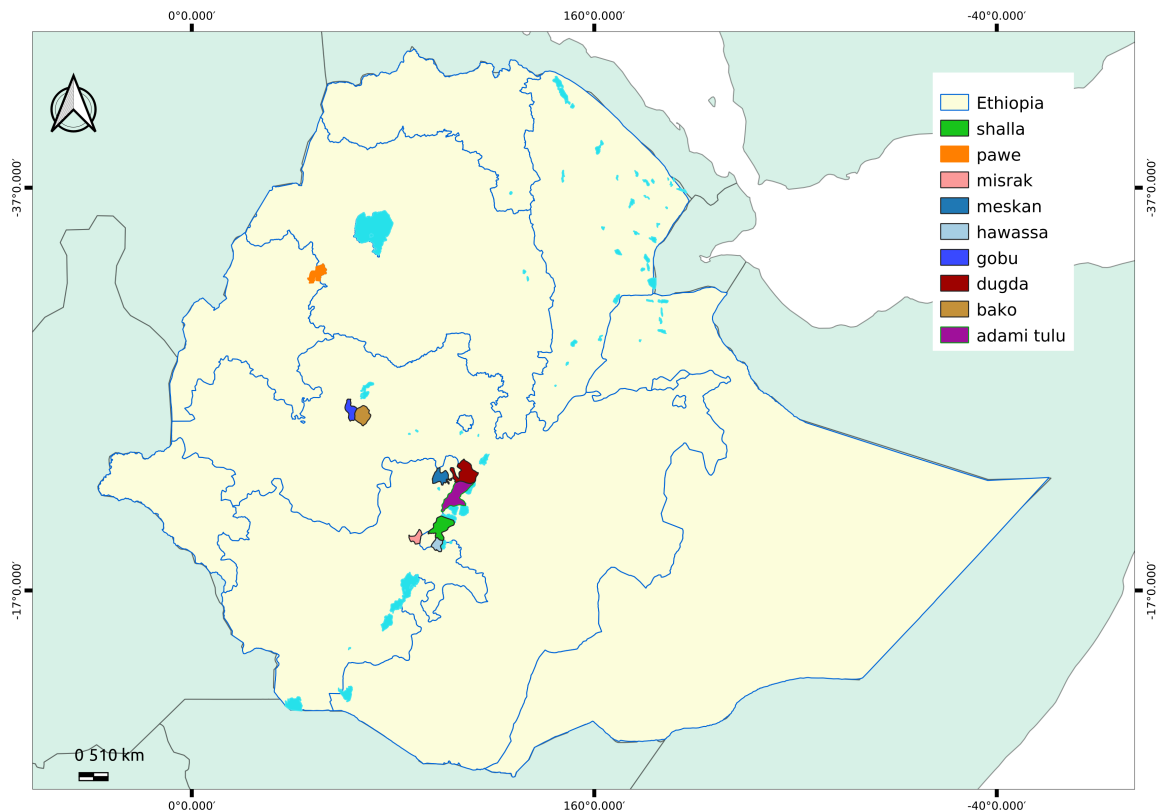


Figure 2.1: Sampling area: CIMMYT survey

The second sample covers a relatively narrower area focusing on smallholder farmers in Ethiopia's northwestern highlands. The sample covers areas under the Nile basin (encircled by the river Nile) and around the Choke mountain range. The data was collected by the student researcher in 2018. The whole sample includes four zones in the Amhara region - Awi, East Gojjam, South Gondar, and West Gojjam. A total of 354 smallholder farmers were selected randomly and a comprehensive farm household survey was administered. The data includes information on household composition and demographics; participation in rural institutions; access to service and infrastructure; social networks; plot level data on agricultural production, input use, yield, marketing and utilization; agroforestry; production constraint; food consumption and expenditure; consumption preference; non-food expenditure; food security; credit and savings; access to extension services; agricultural and non agricultural assets; livestock ownership; income and income sources; and data on shocks, risk management and coping measures. The survey also includes focus group discussions, key informant interviews and case story interviews.

This data is used to initialize the farm decision model to investigate smallholder farmers' mitigation and adaptation of climate variability induced shocks. From the whole sample only 72 farmers in Acacia Decurrens and Bamboo growing Fagita Lekoma district in Awi Zone in Amhara National Regional State to parametrize are used to initialize the model. Figure 2.2 shows sample area of the farm decision model.

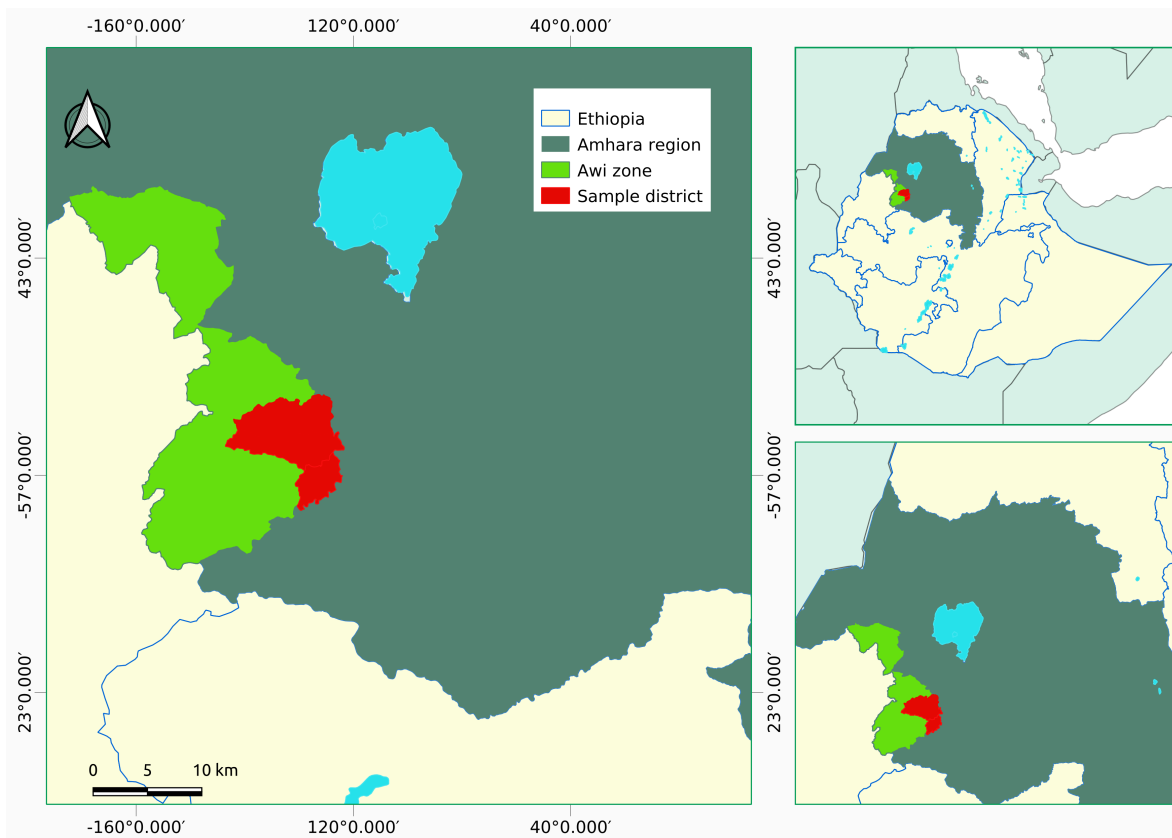


Figure 2.2: Sample area: 2018 survey

2.2 Farming system

This section provides a brief introduction of the farming system the farm decision model is built for. The study area's farming system is called the Western Highland Maize Mixed Farming System (WHMFS). It extends from Awi Zone to East Metekel and East Wollega. As per the 2010 projections, the total population in the whole farming system is around 4 million, 87% of which is agricultural. More than one third of the agricultural population in the area earns less than 1.25 USD per day and, therefore, are considered "rural poor" which accounts for 5% of the country's rural poor. The farming system is dominated by a cool/sub-humid agro-ecological zone with an average elevation of 1,340 meters above sea level (ranging from 528m - 3,145m). The average length of the growing period (LGP) is 219 days ranging from 166 days to 260 days. The average annual rainfall in the area is 1,458 mm (1,057mm to 1,657mm) (Auricht 2017).

Agriculture in the area is dominated by smallholder farmers who practice an integrated crop, livestock and tree perennial production. Teff, finger millet, niger seed, wheat, and barley are the common crops grown in this farming system. Potatoes, tomatoes, and pepper are the common vegetables grown. The common perennials are mango, pawpaw, and coffee. As it is more relevant for this study, the Awi subsystem in the WHMFS has peculiar characteristics where potatoes and barley are the common crops grown. Figure 2.3 shows farming system the farm decision model is built for.

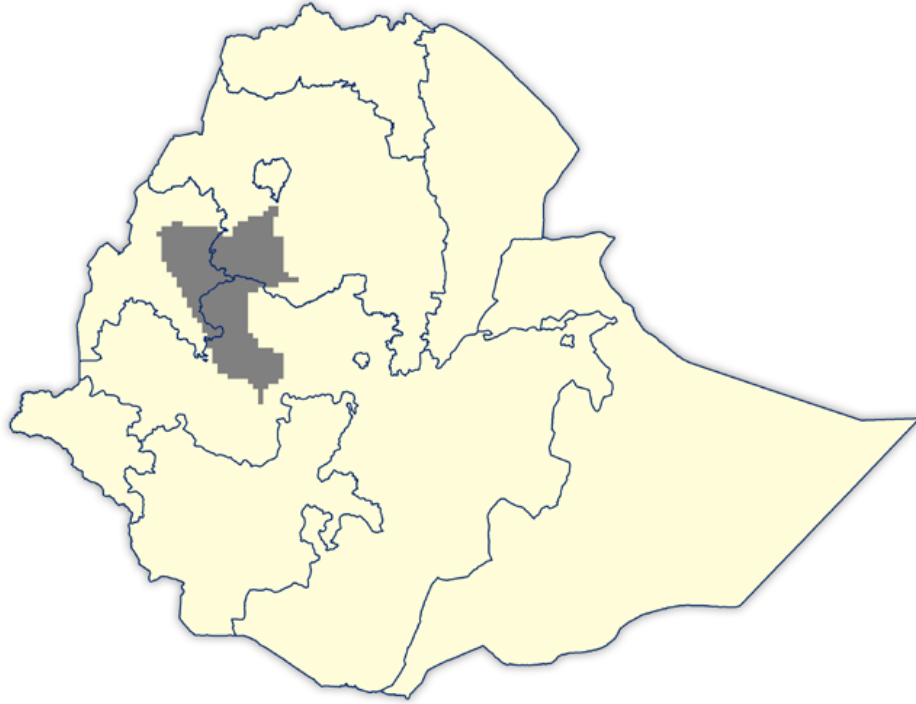


Figure 2.3: Western Highland Maize Mixed Farming System

Farmers in the WHMFS also keep livestock in addition to crops and trees. There is a large population of livestock in the area, mainly equines (horses and mules), cattle and small ruminants (sheep). The primary source of fodder for livestock are crop residues, pasture from private land and communal grazing land. The subsystem is also known for extensive plantations of short-cycle small-scale agroforestry. The major tree perennial farmers grow at a large scale and with commercial orientation are *Acacia Decurrens*, Bamboo and Eucalyptus.

2.3 Methodology

The research applies an integrated approach by blending agent-based modeling and econometric analysis to examine farmers behavioral responses towards climate variability induced shocks and the resultant effects on their livelihoods. On the one hand, using econometric analysis enables us to understand what farmers are currently

doing and the determinants of their behavioral responses (who does what) to mitigate and adapt to shocks. On the other hand, using agent-based modeling, we can model what farmers might do in different situations and analyze potential improvements and optimal responses. Combining these methods enables us to have a holistic perspective on the effects of climate variability-induced shocks on smallholders' livelihoods and their past, current and future behavioral responses to mitigate and adapt to these shocks. The following sections discuss the methods used in this research.

2.3.1 Modelling interdependent adaptation decisions

The research combines logistic principal component analysis (LPCA) (Landgraf and Lee 2015 ; Song et al. 2019) and multivariate probit regression (Khanna 2001 ; Dorfman 1996) to examine determinants of the choice of ex-ante and ex-post measures of smallholder farmers in response to climate variability induced shocks in Ethiopia.

Principal Component Analysis (PCA)

Dimensionality reduction of binary data

The research applies PCA to obtain low dimensional data on farmers' choice of ex-ante and ex-post measures¹ for multivariate probit analysis (MVP). It is used to identify dominant ex-ante and ex-post strategy choices of farmers and to determine their correlation. PCA reduces dimensionality by identifying orthogonal components representing a set of measures that explain a large share of the total variance in the data. This enables us to characterize which set of measures are complementary or substitutes by examining their correlation (Jolliffe 2002).

For PCA, our data is represented by a $n \times k$ matrix of binary responses in which each entry in the matrix represents the adoption of a strategy. Where n is the number of farm households in the sample who faced a particular risk factor in the past ten years (2001-2010) and k is the number of strategy choices available for them in response to the risk factor before and after occurrence. With such a binary choice matrix, the application of classical linear principal component analysis (PCA) to our problem would be misleading (Landgraf and Lee 2015; Jolliffe 2002; Song et al. 2019). PCA is best suited for continuous data. It considers the 0s and 1s in our choice matrices as numbers instead of choices and tries to solve orthogonal principal components as a linear combination of all the measures included in the matrix (Zou, Hastie, and Tibshirani 2006; Jolliffe 2002).

PCA assumes a Gaussian distribution and doesn't account for mathematical properties of binary data - as Gaussian assumptions are only appropriate for continuous numerical data (Landgraf and Lee 2015; Leeuw 2006; Michael, Dasgupta, and Schapire 2002). Nonetheless, there are well-suited methods for dimensionality reduction of binary data that assume binary distribution instead of normal distribution (Tipping and Bishop

¹Throughout the text, ex-ante and ex-post measures refer to adaptation and coping measures respectively.

1999). The popular methods in such respect are logistic PCA (LPCA) and logistic singular value decomposition (LSVD) (Song et al. 2019; Landgraf and Lee 2015; Zou, Hastie, and Tibshirani 2006; Jolliffe 2002). The main difference between the two is whether the score matrix and the loading matrix are estimated simultaneously or sequentially (Song et al. 2019). In LSVD these matrices are estimated simultaneously while LPCA, on the other hand, only estimates the loading matrix directly, and the score matrix is obtained by a projection-based approach in the same manner as classical PCA (Udell et al. 2016; Michael, Dasgupta, and Schapire 2002).

The study applied LPCA and dominant measures are selected based on their component loadings from the first two principal components. The identified dominant measures are later used as dependent variables in the MVP regression model to disentangle farmer-specific determinants of strategy choices for climate variability induced shocks.

Multivariate probit model

Attributed to their unobserved characteristics, smallholder decisions on choice of ex-ante and ex-post measures are interrelated and interdependent to one another (Abay et al. 2018). For example, on the one hand, farmers can choose either to sell tree perennials or to sell livestock as a coping strategy to escape the adverse effects of drought on their livelihoods. On the other hand, they may engage in off-farm activities instead of reducing consumption as a strategy to cope with a hailstorm. To identify the determinants of farmers' choice of ex-ante and ex-post measures with such adoption interdependence, the appropriate estimation method is the multivariate probit model (MVP) (Khanna 2001 ; Dorfman 1996).

MVP has been applied to different interdependent adoption decision problems (M. Kassie et al. 2013; Kpadonou et al. 2017; Tongruksawattana and Wainaina 2019; Teklewold, Gebrehiwot, and Bezabih 2019; Bedeke et al. 2019; Abay et al. 2018; Tsegaye et al. 2017). MVP enables us to capture correlations amongst error terms of adoption equations and estimates a set of binary equations altogether. When the error terms of adoption equations are correlated, estimation using a univariate probit model will produce biased and inefficient coefficient estimates (Belderbos et al. 2004; Dorfman 1996; Khanna 2001). This is the primary advantage of MVP over univariate probit models. Correlations amongst the error terms of adoption equations arise due to the unobserved characteristics of smallholders, affecting their choice of adaptation and coping measures (Greene 2003; Khanna 2001). Positive correlation among adoption equations implies complementarity of the measures, whereas negative correlations imply the measures are alternatives (Khanna 2001). If the error terms are correlated in either of the cases, then the adoption decisions of smallholders are interdependent.

Two underlying processes represent the multivariate decision choice problem of smallholders in MVP. The first is a system of linear equations representing farmer expectations for adopting each ex-ante or ex-post strategy. In this system of equations, the dependent variable is a latent variable (Y), which represents a farmer's expected benefit from adopting a strategy. The expected benefit is realized in terms of increased production and improved farm profits (in the case of ex-ante measures), or consumption

smoothing (in case of ex-post measures) that inturn is a function of farmers observable characteristics at an individual (head) level (IN), a household level (HH) and village or community level (CM) and a multivariate normal stochastic error term (u).

Therefore, the expectation equation for the adoption of adaptation and coping measures is given by:

$$Y_{hk}^* = IN_{hk}\alpha_k + HH_{hk}\beta_k + CM_{hk}\gamma_k + u_{hk} \quad (2.1)$$

Where the $*$ shows that Y is a latent variable; α , β , γ and are parameter coefficients; subscript h represents household level variables and k represents the number of measures (and thus number of system equations) in the model.

The second process describes a farmer's choice of an ex-ante and ex-post measures. Smallholders adopt an ex-ante or ex-post strategy if they expect they would reap a positive benefit from it. The dichotomous choice of ex-ante and ex-post measures is given by:

$$Y = \begin{cases} 1 & \text{if } Y_{hk}^* > 0 \\ 0 & \text{Otherwise} \end{cases} \quad (2.2)$$

The error terms of farmers adoption equations have a joint normal distribution with 0 mean and conditional variance of an identity matrix.

$$(u_1 + u_2 + \dots u_k) \sim MVN(0, \Omega) \quad (2.3)$$

The variance covariance matrix is given by,

$$\Omega = \begin{bmatrix} 1 & \rho_{12} & \dots & \rho_{1k} \\ \rho_{21} & 1 & \dots & \rho_{2k} \\ . & . & \dots & . \\ \rho_{k1} & \rho_{k2} & \dots & 1 \end{bmatrix} \quad (2.4)$$

where ρ represents the pairwise correlation coefficient of the error terms. If the off-diagonal elements in Ω are non-zero, the error terms are correlated, measures are interdependent, and equation 2.2 become a multivariate probit model. If ρ is positive, then the measures are complements and if it is negative then they are substitutes (Khanna 2001). While selecting the explanatory variables in the multivariate probit model precautions are made during model specification not to include two or more explanatory variables which partialy explain the choice of explanatory variables. This helps to avoid the problem of endogeneity in the model.

The results obtained in the PCA and MPV are used as an input to parametrize the agent-based model and later to validate results from simulation experiments. During model parametrization, the most frequent risk factors are included as covariate shocks. The dominant measures obtained from PCA are also used in the model as ex-ante planning options and ex-post responses to shocks. Results from MVP, i.e., farmer-specific drivers of choice of measures, are used as a benchmark to validate the model's corresponding results.

2.3.2 Bioeconomic modelling: Model design and parametrization

The econometric analysis establishes a descriptive analysis of farmers' behavioral responses to climate variability induced covariate shocks. This captures the behavior of farmers in the status quo. However, it does not tell us much about how farmers would behave in different future circumstances, especially with climate and price variability. This requires a prescriptive approach and a detailed investigation of farmers' behavior down to the plot level. To achieve this objective, an agent-based model is developed representing smallholder farmers in the Nile basin's northwestern highlands in Ethiopia. The farmers in the area are known for their integrated crop-forest-livestock system. Tree perennials, mainly *Acacia Decurrens* and Bamboo, are grown intensively in the area. The area is known for its *Taungya* system based on these tree species.

Accordingly, this research applies household level microsimulations to analyze ex-ante planning and ex-post responses to future climate and price variability with a special focus on the role of smallholders' investment in woodlot perennials to their livelihoods. The agent-based simulation package called Mathematical Programming-based Multi-Agent Systems (MPMAS) is used to capture production, consumption and investment decisions at the farm household level. MPMAS is well suited for the analysis of the effect of climate variability in agriculture (Berger and Troost 2014). In their paper, Berger and Troost showed potential application areas for agent-based simulation experiments based on multi-agent systems (MAS). MAS provides a platform for integrating risk components in farm operations and the effectiveness of adaptation measures applied. This includes integration of ex-ante planning for shocks. Coupled with other biophysical models, MAS provides a state of the art analysis of land-use change and supply response in agriculture. MAS is also suitable for ex-ante policy analysis. With the nature of future climate and price variability, MAS allows us to integrate climate variability in ex-ante policy analysis efforts.

The MPMASQL4 software structure and farm decision model and equations are based on the ODD (Overview, Design concepts and Details) protocol following Schreinemachers and Berger (2011). Details on the farm decision model are provided in **Appendix A**.

Overview and Design Concepts

MPMAS allows simulating many heterogeneous farming households' decisions and their consequences under different climatic and economic developments over time, including

interactions between households and their environment. MPMAS is employed in its newest yet unpublished version, which incorporates explicit intertemporal planning and allows us to capture perennial planting and livestock (dis)investment decisions more realistically.

A recursive dynamic intertemporal planning model is developed using plot-level data collected from farm households in Ethiopian highlands in 2018 to capture farmers' multiperiod investment in woodlot perennials alongside their annual non-separable production and consumption decisions. The central component of the modeling framework is a mathematical programming-based decision model that captures the choice of farming households among the available decision alternatives for crop production, livestock raising, perennial and forestry plantations, crop sales, food purchases and consumption, savings, livestock sales and purchases, loan contracting, labor sharing, off-farm labor and temporal migration as well as participation in various forms of informal social safety nets.

The household's main goals are to satisfy its food demand in nutritional energy, ensure survival in bad years, and cover other non-food minimum expenditures. Once these main goals are fulfilled, maximize freely available cash. The farmers' decisions are constrained by its resource base, household labor, production and off-farm employment options, market access, human and social capital, and cultural constraints on labor and consumption, which are established from the results of the econometric analysis. The decision model captures both the ex-ante decision situation where the farming household plans for the coming season and beyond, whereas the ex-post decision situation where the agent has to cope with the potentially adverse outcomes of the cropping seasons.

The decision model is solved recursively in each simulation period for all computational agents in the model which represent farmers in the study area. Decision modeling provides a dynamic platform to analyze agents decisions in the face of different climate, economic and policy development related trajectories. The endogenously determined decision of agents are combined with other exogenous variables to update agents' resource base for the next period. MPMAS also allows adjustments of plans in the beginning and end of each period depending of the outcomes from the previous period. Agents can adjust their production, consumption and investment plans accordingly. The farm decision model also captures the evolution of food and nutrient requirements, labor supply and human capital status of the household by tracking demographic dynamics in the household across simulation periods.

Outcome variables of the household such as income, food security or nutritional status or deficits and deficiencies of these outcome variables can be analyzed using MPMAS. Furthermore, the household dynamics in the decision model allows to undertake gender specific analysis on the output. Figure 2.4 shows conceptual model of farmers decision problem.

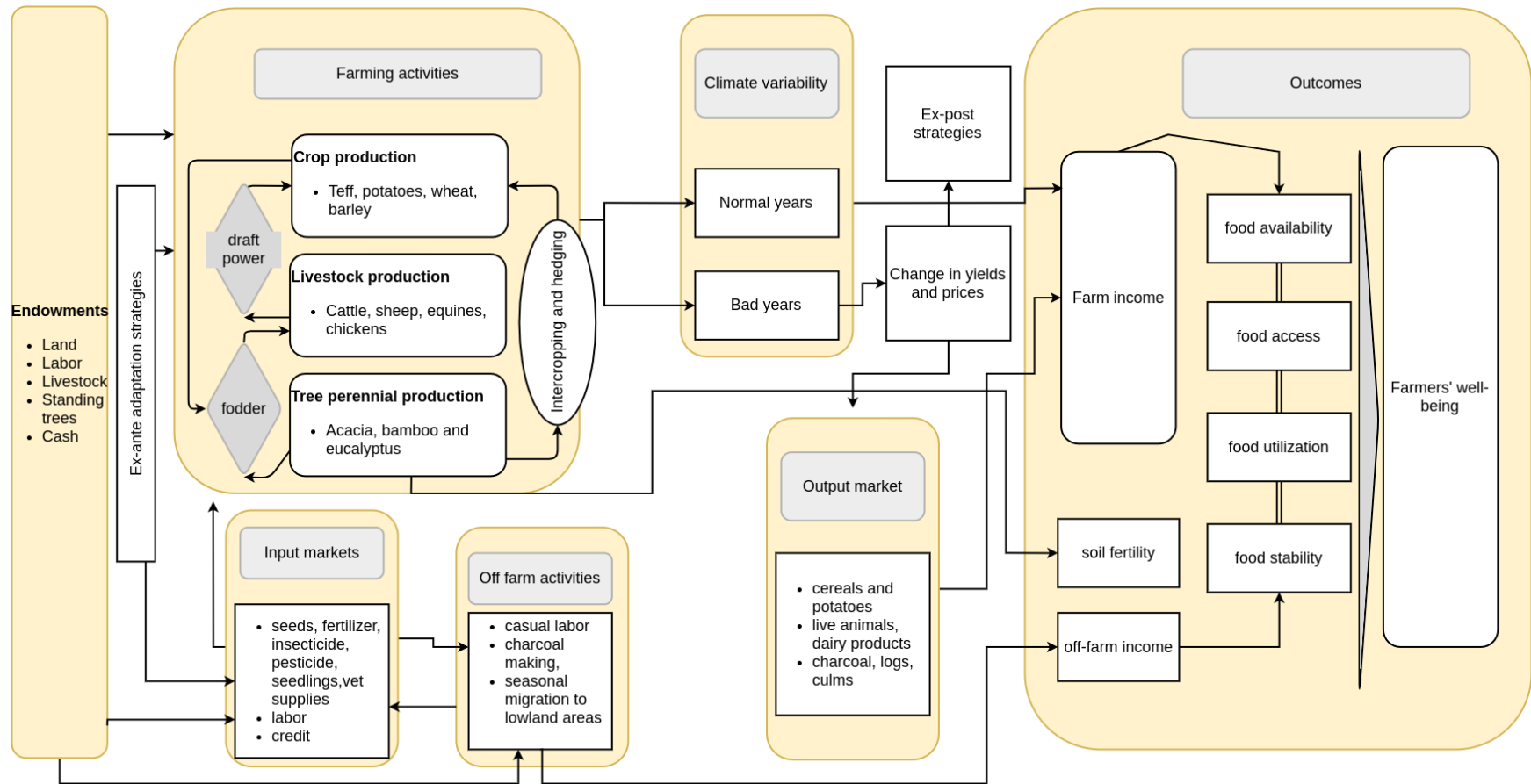


Figure 2.4: Conceptual model of farmers decision problem

Details: *Implementation, initialization and input data*

The farm decision model applied for this research is a recursive dynamic multiperiod model with intertemporal planning (see Figure 2.5). It is a mixed-integer programming (MIP) model where there are several integer constraints. The model captures an integrated farming system where agents engage in crop production and investments in livestock and woodlot perennials. The cool humid (*dega*) agroecological zone in the Awi zone of Amhara region is represented in the model. In the model's current setting, the planning horizon is 15 years, mainly because of multi-period investment decisions.

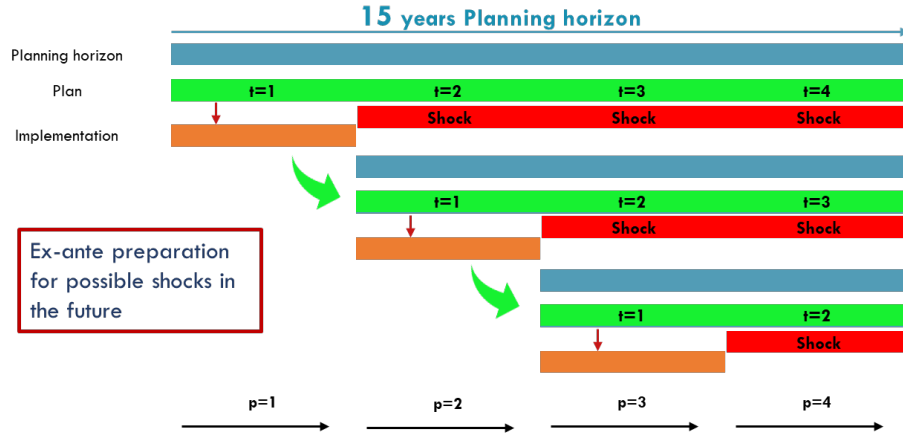


Figure 2.5: Recursive dynamic model with intertemporal planning and ex-ante shock planning. Source: mpmasql4 tutorial (Troost 2021)

t : planning period – shifts from year to year and p : simulation period (fixed)

As shown in Figure 2.5, the model takes agents risk considerations into account (C. Troost 2021). Shocks in the model are represented by bad years. There are many risk factors included in the model (drought, diseases of teff, wheat, potatoes, barley, and acacia seedling). As a result, agents optimize the expected cash surplus only after ensuring current and future minimum consumption needs are fulfilled and adequate precautions are taken to shocks (see the agent's objective in **Appendix A**).

Initial agent information in the model is obtained from the sampled farmers in the 2018 survey. The 72 farmers in the field are represented by 72 agents in the model on a one to one basis. The survey provides initial asset endowments of land (farm size), labor (household composition and age structure), livestock ownership, perennial (standing tree) ownership and capital (cash). Qualitative data about the main practices and principles of farming specific to using focus group discussions and key informant interviews is also collected. As a result, very relevant information on the accustomed rules of farming in the area is obtained, such as rotation patterns, social networks and cropping calendars. Time series data on yield and prices is collected from Ethiopia's central statistical agency (CSA). Data on the interest rate, inflation rate, the wage rate for casual laborers is also obtained from secondary sources.

Agents can grow 4 main crops (wheat, teff, barley and potatoes) in acidic soil type in 2 varieties (local and improved) and 2 fertilization types. There is a total of 38 applicable cropping activities for agents. Inputs of crop production are land, labor, fertilizer, seed, draft power and or cash and the outputs are grain and stover.

Agents also invest in livestock. There are 7 livestock types from cattle, sheep, equines (cow, bull, ox, ram, ewe, horses, mules), which have a lifetime of 6 to 9 years, that agents can invest. Livestock activities in the model are livestock production inputs such as feed, labor, housing, and others (variable cost). Products from investment in livestock are live animals, meat, milk, cheese and butter.

Furthermore, agents invest in woodlot perennials. There are 3 woodlot perennials (acacia decurrens (AD), eucalyptus and bamboo), cycle (first, second), seedling density (high, normal, low) available as options for investment (with a lifetime ranging from 4 to 10 years). There is an accompanying activity of intercropping in the 1st year of AD (red teff, potatoes, barley, wheat) where there are 24 applicable agroforestry activities and also hedging with bamboo. Inputs of woodlot perennial production without intercropping are land, labor, and or cash. Products of investment in perennials are charcoal, logs, culms and/or leaves.

Details on the farm decision model are provided in **Appendix A**.

Methods of model validation

Validation is an essential step in agent-based models. However, there is no single best method recommended to validate an agent-based model. Besides, given the complex systems modeled in ABM, a single validation procedure alone might not be sufficient (Troost and Berger 2020). Hence, validation techniques should be tailored to the objectives of a specific research context (Troost and Berger 2020). In this context, this research uses empirical and interactive methods to validate the farm level programming model to lay a solid basis for simulation experiments, ensuring the reliability of results and enhancing the predictive quality of farm-level micro-simulations. The general framework of model validation resides on comparing actual and simulated results of primary outcome variable such as land-use between surveyed farmers on the field and agents in the model on a one to one basis. For the empirical validation, the survey data collected in 2018 is used. Figure 2.6 shows the general framework and approach for model validation.

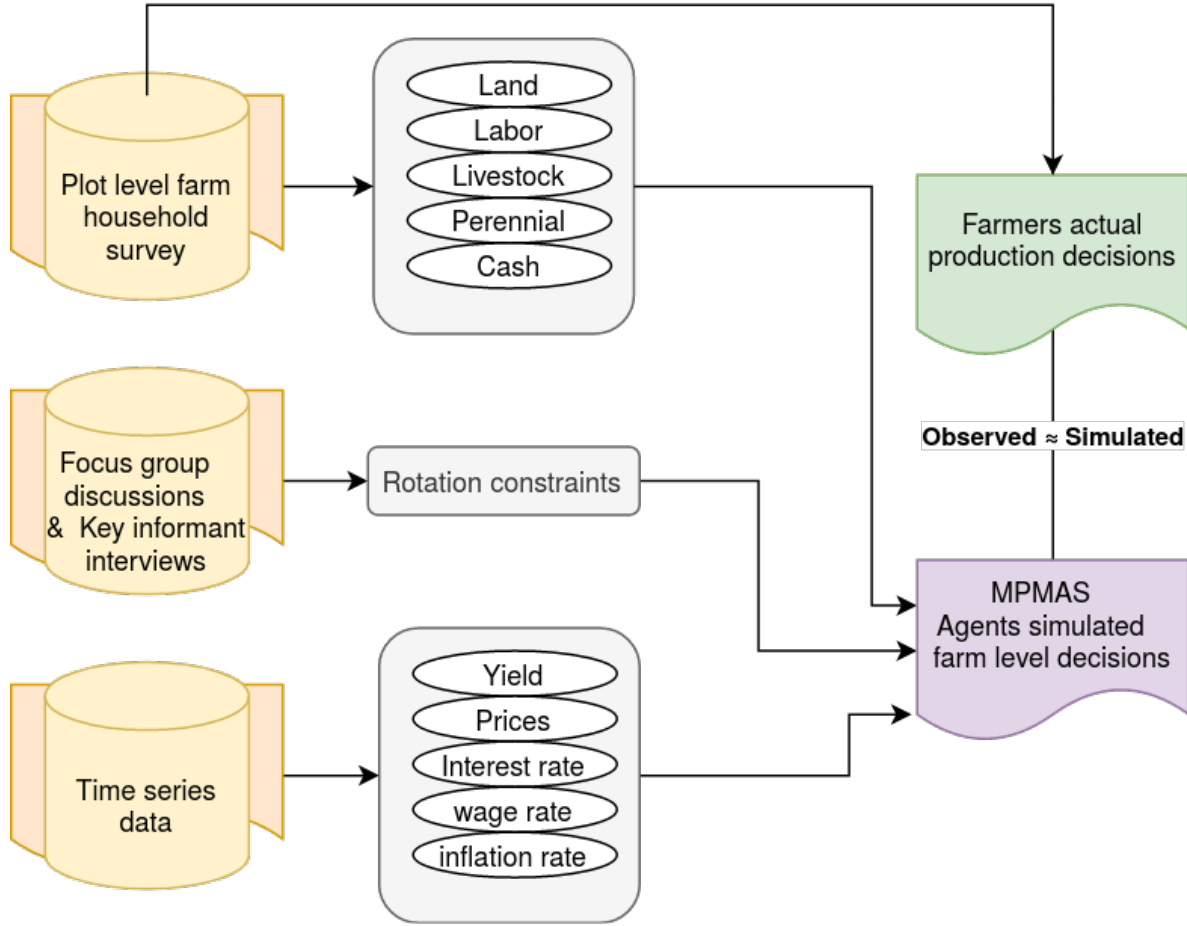


Figure 2.6: Model validation framework

Interactive model Validation

Comparing multi-period simulation results with observed survey results obtained at a given snapshot in time might not adequately show the model's validity. Two reasons can be mentioned for this. First, each period's simulation result obtained from the model is loaded with information on planned activities in the future and feedback from the previous periods - especially in the presence of long term investments such as perennials. Each period simulation result might have a different level of goodness of fit for the observed data. This leads to an underestimation or overestimation of the observed results. Second, cross-sectional data obtained in the survey (which is used as a benchmark for validation) might not adequately reflect the model's current status. The occurrence of both idiosyncratic and covariate shocks, for instance, might have a seasonal divergence of outcomes captured during the survey but might not reflect the status of the farmer in general. Since the model's parameterization is largely dependent on this survey, the validation results might be skewed based on temporary shocks. This will in turn overestimate or underestimate validation parameters.

To avoid such data-driven discrepancies in validation results and to consolidate the

results obtained from the empirical validation, a participatory and more interactive model validation method had to be applied. Initially, the interactive validation was designed to be conducted with farmers who participated in the survey. However, because of COVID-19, it was not possible to conduct a modeler-to-farmer interactive validation. As a result, an alternative design was devised - an online participatory platform to validate the model using experts in various agricultural fields in Ethiopia. The objective was to improve further/sharpen the empirically validated model using feedback from experts from different fields of agriculture. The selection of experts was based on the relevance of their expertise, particularly to our model and their experience working in the area. There were participants from the fields of crop science, rural development, forestry, and agricultural economics.

To undertake this modeler-expert participatory validation, an interactive web application was developed using R Shiny. The app is designed as a web page where all participants were sent the link and could open it using any device they wish to use. For convenience the interactive session was guided by the researcher through a video conference. All the necessary simulations were run ahead. The required data for model validation is uploaded in advance to the server. The app operates at minimal internet data requirements which is suitable for the poor internet connectivity in Ethiopia. This reduces the validation time compared with the previous versions of interactive MPMAS validation (Mössinger et al. 2022), where the model has to run on the field for all designed points used for model validation on the spot.

Results of model validation are discussed in chapter four.

Chapter 3

Farmers' adaptation to and coping with climate variability-induced shocks in Ethiopia

Disentangling household specific determinants of ex-ante and ex-post strategy choices

Chapter objectives

- *Identifying farmers' choice of dominant ex-ante and ex-post measures for the most frequent and intense climate variability induced shocks*
- *Examining household specific drivers of measures*
- *Examining complementarity and substitutability of measures*
- *Identifying feedback from the results to be used as an input for the farm decision model*

Establishing smallholder farmers' existing behavioral responses to adapt and mitigate with climate variability-induced shocks is the first objective of this thesis. Knowing the current adaptation and mitigation practices and disentangling farmer-specific determinants of choices of these practices helps to understand robust strategies. Besides, it also helps to draw lessons later used to build the baseline farm decision model for ex-ante analysis. As a result, this chapter presents results from the econometric analysis and aims at establishing this knowledge. First, the most frequent and intense climate variability induced risk factors are selected and farmers' dominant strategy choices for each risk factor is identified. Second, farmer specific drivers of choices of dominant measures are examined to capture farmer heterogeneity in choices. Third, complementary and substitute measures are identified based on the

criteria of competition over the same resource. Fourth, correlation between ex-ante and ex-post measures are examined to see the success of ex-ante measures. Finally, important lessons from the econometric analysis are identified to be used as an input to parametrize the farm decision model presented in the subsequent chapters.

3.1 Farmers' dominant ex-ante and ex-post strategy choices

3.1.1 Risk factors

During the data collection, farmers in the sample were provided with different names of risk factors. First, they were asked to report if the risk factor had occurred in the previous ten years (2000 - 2010). Then, second, if it had occurred, how many times it occurred during that time period. If they reported a risk factor during the specified ten years period, third, they were asked to choose three most important measures they adopted for each risk factor before and after its occurrence. Farmers have also reported which of the risk factors were more intense and disastrous and which were relatively easy. Based on farmers' responses the most frequent and intense risk factors are identified as shown in Table 3.1.

Table 3.1: Most frequent and Intense risk factors

Risk Factor	Frequency of occurrence between 2000 to 2010 (average frequency)	Stress Intensity (%) (Reported as very stressful by farmers) – plot level
Drought	2.12	43.58
Crop pests and disease	1.85	33.1
Hailstorm	1.75	8.72
Flood	1.68	0.65
Observations	898.00	3,715

Risk factor intensity is as important as frequency of occurrence (El Kenawy et al. 2016; Bewket and Conway 2007). For instance, an occurrence of hailstorm in a season might have a more distressing effect than two consecutive crop pest years. This is the main reason why risk factor frequency and intensity are considered together to select the most pressing risk factors for analysis. As a result, drought, crop pests and diseases and hailstorm are considered as the most frequent and intense risk factors. All the above risk factors are covariate shocks which occur at village level and their devastating effect is shared by households in the same village. Drought typically has a larger area of impact than hailstorms and pests (Nguyen and Minh Pham 2018).

Ex-ante and ex-post measures were used in logistic PCA to identify farmers dominant choices for multivariate analysis and to identify correlation between measures. This is done for drought, hailstorm and pests and crop disease before and after occurrence and the results are summarized in Table 3.2 and Table 3.3. From 898 sample households,

730 of them reported drought has occurred in their village in the past 10 years. Whereas episodes of hailstorm and pests or crop disease are reported by 432 and 613 farmers, respectively. LPCA was run on measures and results show that the proportion of variance explained by the first two components explain a large proportion of the total variance in the farmers choice matrices, ranging from 60.7% to 88%. The highest contributing measures to the total variance in the choice matrix were selected based on the value of their component loadings. Table 3.2 and Table 3.3. shows LPCA component loadings of measures. The first three or four measures with the highest component loadings are considered as dominant measures. Most of which have loadings of ≥ 0.4 .

Table 3.2: Component loadings of the first four principal components for logistic PCA: Ex-ante

Strategy	<i>Ex-ante principal component loadings</i>					
	Drought		Hailstorm		Pests	
	pc1	pc2	pc1	pc2	pc1	pc2
Drought tolerant crops (DTC)	0.54	0.16				
Drought tolerant varieties (DTV)	0.47	0.30				
Early planting (EP)	0.21	0.53	0.10	0.06	0.31	0.47
Crop diversification (CD)	0.02	0.04	0.29	0.53	0.44	0.43
Increase seed rate (ISR)	0.19	0.10	0.65	0.01	0.38	0.25
Offfarm work (OF)	0.18	0.41	0.38	0.52	0.05	0.01
Saving (SA)	0.49	0.13			0.35	0.03
Soil and water conservation (SWC)	0.03	0.55	0.34	0.47	0.07	0.06
Planting local varieties (LV)			0.47	0.25	0.38	0.30
Water harvesting (WH)	0.07	0.04				
Rented out land (ROL)	0.07	0.04				
Planting trees (PT)	0.33	0.31	0.01	0.36	0.02	0.00
Cooperative membership (EC)			0.06	0.18		
Pest and crop disease tolerant varieties (PTV)					0.44	0.40
Ask for expert advice (EXA)					0.01	0.00
Use pesticide (PES)					0.30	0.53
Explained variance (%)	78.50		88.20		82.10	
Sample size	730.00		432.00		613.00	

Table 3.3: Component loadings of the first four principal components for logistic PCA:
Ex-post

Strategy	<i>Ex-post principal component loadings</i>					
	Drought		Hailstorm		Pests	
	pc1	pc2	pc1	pc2	pc1	pc2
Replanting (RPL)	0.47	0.31	0.29	0.50	0.06	0.03
Selling livestock (SL)	0.42	0.42	0.48	0.02	0.51	0.31
Rent out land (ROL)	0.01	0.03	0.04	0.18		
Selling assets (SAS)	0.19	0.50	0.02	0.16	0.50	0.31
Reduce consumption (RC)	0.41	0.32	0.56	0.07	0.07	0.58
Outmigration (OM)	0.05	0.10			0.26	0.24
Borrowing (BR)	0.06	0.04	0.22	0.46	0.07	0.06
Stop sending children to school (SSCTS)	0.36	0.23	0.40	0.28	0.06	0.10
Offfarm work (OF)	0.28	0.47	0.20	0.53	0.50	0.03
Herbicide and pesticide (HP)					0.15	0.50
Government assistance (GA)	0.05	0.01	0.10	0.28	0.09	0.29
Used stored crops (USC)	0.03	0.25			0.21	0.15
Received aid (AID)	0.43	0.11	0.33	0.14	0.29	0.20
Dissaving (DI)	0.02	0.10	0.02	0.10		
Explained variance (%)	60.70		64.20		61.30	
Sample size	730.00		432.00		613.00	

Based on results from Table 3.2 and Table 3.3., the dominant measures identified by LPCA are summarized in Table 3.4. Crop management activities such as planting stress resistant crops and varieties, early planting, increasing seed rate and soil and water conservation practices are the dominant ex-ante measures for climate variability-induced shocks Farmers also engage in off-farm activities to supplement their income for shocks such as hailstorm. Selling livestock, selling assets, reducing consumption, borrowing and replanting are the dominant ex-post measures for climate induced shocks. Measures identified in Table 3.4 are used as dependent variables in MVP regression.

Table 3.4: Dominant measures (logistic PCA) and their frequency in the sample

<i>PCA chosen dominant measures and their frequencies in the sample</i>					
Risk factor	Ex-ante		Ex-post		
	Strategy	Frequency (%)	Strategy	Frequency (%)	
Drought	Planting drought tolerant crops	23.3	Replanting	25.9	
	Planting drought tolerant varieties	18.2	Selling livestock	34.8	
	Early planting	9.2	Selling other assets	14.5	
	Soil and water Conservation	6.3	Reduce consumption	22.2	
Hailstorm	Crop diversification	6.7	Replanting	22.2	
	More nonfarm work	4.4	Selling livestock	14.4	
	Increase seed rate	6.7	Reduce consumption	20.4	
Pests	Plant disease/pest tolerant varieties	28.5	Borrowing	12.7	
	Crop diversification	13.2	Selling livestock	13.0	
	Increase seed rate	4.9	Selling other assets	14.8	
			Eat less than before	15.7	

3.2 Drivers of farmers ex-ante and ex-post coping strategy choice

Explanatory variables used in the MVP regression are described (with the rationale for inclusion in the model specification) in this section before the results are presented. The model presumes that farmers' choice of a given strategy is subject to quantity and quality of human capital they have in the household; their social networks and participation in rural institutions; access to market and extension services; asset endowments they have and their experience and expectation related with shocks (M. Kassie et al. 2013; Tongruksawattana and Wainaina 2019; Teklewold, Gebrehiwot, and Bezabih 2019; Bedeke et al. 2019; Abay et al. 2018; Tsegaye et al. 2017). The dependent variables for the MVP model, on the other hand, are obtained from LPCA results.

3.2.1 Description of variables

3.2.2 Explanatory variables of MVP models

Human capital: Human capital plays a crucial role in determining farmers' choice of ex-ante and ex-post measures (Wossen 2018). Human capital of the household in the model is captured using education, age and gender of household head and total family size. The average literacy rate in the sample is 57%. Educated households may have more knowledge about adaptation and coping strategy options than uneducated farmers and are expected to be more open to new farm innovations in such regard. Educated farmers may also have better expectations of future droughts and thus may be better prepared. Age of household head may have high correlation with farming experience and knowledge. The average age of household head in the sample was 44 years old. Older household heads are expected to be more resilient than younger household heads. Gender of household head is highly related with key resource ownership, such as land and labour, in rural Ethiopia (Wossen 2018). Female headed households, on average, have lower resource settings than their male counterparts (Wossen 2018). Resource base of households, on the other hand, has a crucial role in farmer's choice of adaptation and coping measures (Asfaw et al. 2018). Therefore, female headed households may choose less costly or rationing measures whereas male headed households may tend to choose more resource demanding and labour-intensive measures. Interaction variable between gender of the household head and total TLU are also included to capture the effect of gender on choice of measures based on resource availability in the household. In addition, family size may have positive relationship for both ex-ante and ex-post as households with larger families have relatively more labour capacity. This may enable them to choose for alternative off-farm jobs as adaptation as well as coping measures. The average family size in the sample is 6.5 persons.

Table 3.5: Summary of Variables in MVP model

Variable	Description	<i>Risk factors</i>					
		Drought		Hailstorm		Pests	
		mean	s.d	mean	s.d	mean	s.d
Household Attributes							
Human capital							
Gender	1 = household head is male	0.92	-	0.95	-	0.93	-
Age	Age of household head (years)	43.5	12.7	42.65	12.58	43.29	12.67
Education	1 = household head is literate	0.57	-	0 .62	0 .48	0.59	-
Family size	Total family size of the household (persons)	6.5	2.3	6.47	2.34	6.5	2.4
Access to main services							
Market	Minutes of walking time to the market	93.8	62.9	92.17	62.18	92.54	61.2
Agricultural ext. office	Minutes of walking time to the agricultural extension office	30.6	30.9	30.18	29.54	31.58	31.14
Rural Institutions and Social Networks							
Farmer association	1 = farmer is a member of farmer association	0.08	-	0.22	-	0.23	-
Religious association	1 = farmer is a member of religious association	0.15	-	0.28	-	0.32	-
SACCO	1 = farmer is a member of saving and credit association	0.09	-	0.29	-	0.28	-
Iddir	1 = farmer is a member of iddir	0.4	-	0.86	-	0.82	-
Relatives	Number of relatives the farmer can rely on	12.4	16.5	11.06	12.55	12.04	14.36
Friends	Number of friends the farmer can rely on	12.9	21	11.57	19.2	12.5	20.26
Leadership	1 = friends or relatives in leadership position	0.48	-	0.47	-	0.48	-
Resources and assets							
Asset Value	Total Asset value of the household	13,196	19,122	14461.66	22896.19	15787.32	26364.18
Farm size	Farm size of the household	2.03	1.83	3.66	3.65	3.4	3.6
TLU	Tropical livestock unit	8.61	7.26	8.39	8029	8.84	9.42
Food expenditure	Food expenditure in '000 ETB	2.3	1.6	2279.10	1517.13	2364.76	1614.24
Non-food expenditure	Non-food expenditure in '000 ETB	4.9	14.6	4242.21	9819.97	4603.31	12595.94
Credit constrained	1=credit constrained	0.31	-	0.6	-	0.58	-
Extension Services							
Adaptation	1 = receive training or information on adaptation	0.66	-	0.62	-	0.61	-
Varieties	1 = receive training or information on new varieties of maize	0.89	-	0.88	-	0.88	-
Input market	1 = receive training or information on input market and prices	0.72	-	0.69	-	0 .68	-
Shock Experience and Expectation							
Shock frequency (last 10 years)	Drought frequency in the last 10 years	2.6	1.4	2.18	1.55	2.7	2.1
Expectation of shock in the future	1 = if they expect drought in the future	0.59	-	0.63	-	0.57	-
Expectation Frequency	Frequency of expectations in coming 10 years	2.7	1.9	3	2.5	3.2	2.2

Rural institutions and social networks: Farmers' participation in rural institutions and strength of their social ties provide them way outs which would be difficult to achieve without enough resources (Wuepper et al. 2018; Caeyers and Dercon 2012; Dercon and Krishnan 2003; Paul et al. 2016; Adger 2003; Wossen et al. 2013; Wossen et al. 2015). Participation in rural institutions is captured in the model using farmers' membership in *iddir*, saving and credit associations, farmer associations and religious associations. Farmers' participation in these institutions is expected to enable them to get support in terms of farm inputs (labour, farm implements, seed, or knowledge and experience sharing, etc), cash (borrowing) or food (Dercon et al. 2006). Therefore, farmers who are members of rural institutions are expected to mitigate risk better than those who are not. Similarly, farmers social network in the model is captured by the number of friends and relatives they have inside and outside their villages and whether they have a friend or relative in leadership position. Farmers who have more friends and relatives are expected to have more options to choose. They are also expected to smooth consumption and mitigate risk better than others.

Access to market and extension services: Access to input and output markets in the model is captured by their proximity to the main market in the nearby town. Whereas, their access to services and knowledge is captured by proximity of their residence to agricultural extension offices and whether they have been advised or took training on adaptation to climate variability, input markets and varieties. Farmers who are near to the main market are expected to have more off-farm job opportunities than those who are far away (Amare and Simane 2017). They may also have better market information. Farmers near agricultural extension offices and who took training and counselling are expected to have better knowledge and skills and are thus expected to be more resilient (Asrat and Simane 2018).

Resources and assets: Farmers' resource endowments (constraints) in the model are captured using farm size, total TLU, total estimated asset value other than livestock assets, off-farm employment, food and non-food expenditure, previous year stock of food and access to credit. Resource constraints are the prime drivers of the variation in farmers' choices of adaptation and coping measures (Asfaw et al. 2018). Farmers with better resource endowments are expected to be more resilient. Irrigation is also included in the model to show its role in determining farmers choice adaptation and coping measures. Farmers who have irrigated plots have better access to food than others and are expected to be more resilient.

Shock experience and expectation: Ex-ante strategy choices of farmers are highly related to their shock experience and expectation (Robert et al. 2016). Shock experience and expectation in the model is captured using past frequency of shocks, future shock expectation and frequency of shock expectation. These variables collectively capture how farmers choose their adaptation and coping measures in line with the feedback they had in the past years. Farmers who experienced shocks more frequently are expected to have better knowledge on how to cope and adapt.

3.3 Multivariate probit regression results

Multivariate probit regression results show that farmers' human capital, participation in rural institutions and strength of social networks, resource endowments, knowledge and access to extension services and their shock experience and expectation in general are the major drivers for farmers' choice of ex-ante and ex-post measures for climate variability induced shocks. Tables 3.6 - 3.9 show MVP regression results for drought, hailstorm and pests and crop diseases respectively.

Gender of household head has a significant effect in the choice of ex-ante and ex-post drought measures. Male-headed households are more likely to engage in soil and water conservation activities to prevent the adverse effects of drought. They are also more likely to engage in early planting than their female counterparts, but the effect of gender on choice of measures is dependent on household's material wellbeing represented by total TLU. Male headed households apply crop diversification and increase seed rate as an ex-ante preparation for drought and they are less likely to sell livestock after hailstorm. The effect of gender on hailstorm is dependent on the livestock worth of the household. In response to pests and crop disease, male-headed households apply crop diversification and plant pest tolerant varieties to mitigate the adverse effects. Households with elderly heads are related to lower likelihood of selling assets to cope drought. Literacy of household head is related to application of drought tolerant varieties as an adaptation strategy.

Results show that farmers' participation in rural institutions, mainly participation in *iddir* and saving and credit associations, has a significant effect to their choice of adaptation and coping measures for drought and hailstorm. Farmers who are members of *iddir* more likely choose planting drought tolerant crops and early planting as ex-ante drought strategy whereas they are less likely to sell livestock in the aftershock. *iddir* members are also more likely to engage in crop diversification to mitigate the possible adverse effects of hailstorm. Members of saving and credit association are more likely to sell livestock to cope from hailstorm than non-members. The MVP result shows that farmers with more friends or relatives in a leadership position use soil and water conservation activities to counter the adverse effects of drought.

The MVP result shows that farmers resource endowments are important in determining their ex-ante and ex-post coping strategy choices. High total TLU is associated with early planting as ex-ante adaptation strategy for drought. Farmers with higher total TLU are more likely to increase seed rate and engage in off farm activities as an ex-ante hailstorm strategy but are less likely to sell livestock after hailstorm. TLU is also positively related with application of crop diversification for ex-ante preparation for pests and crop diseases. Larger farm size is associated with planting drought tolerant crops to prepare for drought and less likely to reduce consumption to cope adverse effects of pests and crop disease. Higher total asset value is associated with lower probability of early planting for ex-ante drought planning and low probability of selling livestock after drought. Farmers with higher asset values are also less likely to increase seed rate to mitigate hailstorm. These farmers are also less likely to sell livestock to cope pests and crop diseases. Furthermore, households' non-food expenditure has a

significant role for their choice of measures. Those with high non-food expenditure are more likely to engage in early planting as ex-ante drought measures. For hailstorm, households with high non-food expenditure engage in off farm activities as an ex-ante strategy. And, households with high non-food expenditure sell livestock to cope with drought, hailstorm and pests and crop diseases.

Table 3.6: Multivariate probit regression results for drought

VARIABLES	<i>Drought</i>							
	Ex-ante				Ex-post			
	DTC	DTV	EP	SWC	RPL	SL	SA	RC
Model	1	2	3	4	1	2	3	4
Human Capital								
Gender	625	463	2.451***	3.709***	409	347	-117	664
	-429	-381	-625	-260	-342	-319	-405	-427
Gender*TLU	-0.0385	-0.0207	-0.185***	-0.0320	-0.0274	-0.00713	0.00264	-0.0507
	(0.0507)	(0.0501)	(0.0601)	(0.0395)	(0.0433)	(0.0410)	(0.0503)	(0.0467)
Age	0.00120	0.00128	-0.00100	-4.94e-05	0.00674	-0.00341	-0.0102**	-0.00129
	(0.00442)	(0.00483)	(0.00571)	(0.00659)	(0.00429)	(0.00402)	(0.00483)	(0.00455)
Education	163	0.218*	-0.0705	128	0.0197	-0.0622	-179	0.0623
	-121	-125	-153	-172	-110	-104	-124	-114
Family Size	-0.0245	-0.0171	-0.0324	-0.0492	0.000798	-0.00212	0.0215	-0.0313
	(0.0239)	(0.0259)	(0.0368)	(0.0406)	(0.0246)	(0.0240)	(0.0296)	(0.0252)
Access to Markets								
Walking min to main market	0.000131	0.00200**	0.000404	0.00134				
	(0.000901)	(0.000953)	(0.00110)	(0.00143)				
Walking min to main extension office	0.000888	-0.00159	0.000647	-0.000729				
	(0.00171)	(0.00208)	(0.00257)	(0.00262)				
Rural Institutions: Member to Saving and Credit Association	-0.0203	-0.00989	103	-0.00597	0.0381	129	103	111
	-122	-133	-155	-170	-116	-112	-128	-120
Religious Association	-143	-131	-0.0726	-264				
	-119	-126	-149	-163				
Iddir	0.328**	0.251*	0.552***	-0.00997	-0.0774	-0.254**	102	141
	-135	-146	-201	-181	-122	-118	-143	-137
Farmers' association					0.0207	-0.0110	121	-118
					-120	-115	-134	-129
Social Networks								
Total Number of Relatives					0.00240	0.00583	-0.00261	-0.00567
					(0.00432)	(0.00423)	(0.00483)	(0.00448)
Total Number of Friends					-0.00219	-0.00465	0.00265	0.00117
					(0.00359)	(0.00354)	(0.00364)	(0.00344)
Observations	730	730	730	730	730	730	730	730

Multivariate probit regression results for drought: continued

VARIABLES	Ex-ante				Ex-post			
	DTC	DTV	EP	SWC	RPL	SL	SA	RC
Model	1	2	3	4	1	2	3	4
Friends in Leadership Position	163 -109	174 -117	195 -138	0.425*** -160				
Resources and assets								
Total TLU	0.0316 (0.0502)	0.0155 (0.0495)	0.184*** (0.0595)	0.0278 (0.0385)	0.0199 (0.0429)	0.0117 (0.0408)	0.00166 (0.0501)	0.0663 (0.0465)
Farm Size (ha)	0.0402*** (0.0142)	-0.00448 (0.0178)	-0.0268 (0.0271)	-0.00385 (0.0222)	-0.0159 (0.0163)	-0.0221 (0.0152)	0.0185 (0.0160)	-0.00299 (0.0160)
Total Asset Value	0.00251 (0.00282)	0.00129 (0.00280)	-0.0109** (0.00494)	0.00188 (0.00252)	-0.00348 (0.00237)	-0.00709** (0.00287)	-0.00648* (0.00364)	0.00268 (0.00239)
Food Expenditure	-0.0283 (0.0376)	-0.0271 (0.0422)	0.00653 (0.0471)	0.0712 (0.0472)	0.00275 (0.0348)	0.0336 (0.0345)	0.0115 (0.0404)	0.0167 (0.0362)
Non-food Expenditure	-0.00241 (0.00378)	0.00558* (0.00296)	0.00869** (0.00354)	-0.00720 (0.00605)	-0.000889 (0.00461)	0.00702** (0.00299)	0.00536 (0.00437)	0.000151 (0.00405)
Access to Extension Services and Farmers Knowledge								
Took Training on Climate Change Adaptation	-0.218* -112	-0.0938 -117	-0.288** -142	0.597*** -172				
Farmers' Shock Experience and Expectation								
Drought frequency (last 10 years)	0.0469 (0.0393)	0.159*** (0.0385)	-0.102** (0.0484)	0.253*** (0.0503)	0.163*** (0.0360)	0.0936*** (0.0340)	-0.0353 (0.0378)	-0.0259 (0.0376)
Expectation of drought in the future	0.754*** -121	0.640*** -127	0.852*** -179	0.545*** -186				
Expectation Frequency								
Constant	-2.184*** -519	-2.532*** -470	-4.109*** -732	-6.837*** -497	-1.597*** -416	-613 -380	-678 -468	-1.389*** -475
Observations	730	730	730	730	730	730	730	730

Table 3.8: MVP results for hailstorm

VARIABLES	<i>Hailstorm</i>					
	Ex-ante			Ex-post		
	CD	ISR	OFF	RPL	SL	RC
Model	1	2	3	1	2	3
Human Capital						
Gender	1.716*** -542	1.019** -501	-838 -607	1.160* -679	-1.730** -779	582 -603
Gender*TLU	-0.134** (0.0526)	-0.0909* (0.0519)	0.0224 (0.0636)	-0.0924* (0.0541)	0.317** -152	-0.0593 (0.0511)
Age	0.0175** (0.00715)	-0.00317 (0.00758)	0.00742 (0.00792)	0.00369 (0.00550)	0.00274 (0.00602)	-0.00404 (0.00577)
Education	231 -224	0.0656 -208	-0.00544 -236	0.0618 -154	-0.0539 -166	-159 -153
Family Size	0.0225 (0.0441)	0.00805 (0.0406)	-0.0223 (0.0623)	-0.0384 (0.0347)	-0.0218 (0.0355)	-0.0168 (0.0342)
Rural Institutions						
Farmers Association	-226 -285	-204 -262	-0.0202 -320	0.0773 -172	-156 -215	-305 -186
Saving and Credit Association	107 -245	265 -237	-0.0914 -244	-0.0131 -157	0.401** -188	210 -162
Iddir	0.711** -347	202 -271	316 -349	-0.0689 -205	-108 -226	226 -205
eqqub	211 -300	197 -286	237 -310			
Social Networks						
Total number of relatives				0.00637 (0.00548)	0.00222 (0.00578)	-0.0125* (0.00692)
Relatives living in the village	-0.0110 (0.0157)	-0.0387 (0.0250)	-0.000198 (0.0163)			
Relatives living outside the village	0.0259* (0.0138)	0.0202 (0.0164)	0.0234 (0.0155)			
Friends living outside the village	-0.00826 (0.00986)	-0.0101 (0.0143)	-0.0131 (0.0146)			
Resources and assets						
Total farm size	-0.0501 (0.0311)	-0.0199 (0.0324)	-0.0128 (0.0362)	0.0115 (0.0186)	-0.00710 (0.0284)	0.0124 (0.0217)
Total TLU	0.146*** (0.0526)	0.119** (0.0513)	0.00272 (0.0626)	0.104* (0.0538)	-0.317** -152	0.0650 (0.0504)
Non-food expenditure	0.000389 (0.00558)	0.00380 (0.00496)	0.0185*** (0.00432)	-0.00650 (0.00704)	0.01000** (0.00500)	-0.00525 (0.00567)
Food expenditure	-0.0148 (0.0714)	-0.0876 (0.0741)	0.0472 (0.0790)	0.0624 (0.0539)	-0.0256 (0.0578)	-0.0972* (0.0560)
Safety net				-0.0977 -335	-128 -367	0.0411 -299
Total asset value	-0.00768 (0.00534)	-0.0132** (0.00665)	-0.00669 (0.00569)	-0.00103 (0.00307)	0.000634 (0.00333)	0.00202 (0.00355)
Farmers Shock Experience and Expectation						
Hailstorm Frequency	-0.0942 (0.0750)	-0.00489 (0.0545)	-0.0140 (0.0520)	0.135*** (0.0427)	0.200*** (0.0447)	-0.101** (0.0469)
Hailstorm Expectation frequency						
Constant	-4.656*** -742	-2.488*** -665	-1.758** -796	-2.443*** -805	243 -850	-780 -698
Observations	432	432	432	432	432	432

Access extension services and farmers' knowledge has a significant effect on farmers' choice of ex-ante measures to adapt for drought. Farmers who took training and

Table 3.9: MVP results for pests and crop disease

VARIABLES	<i>Pests and crop disease</i>				
	Ex-ante		Ex-post		
	PTV	CD	SL	SA	RC
Models	1	2	1	2	3
Human Capital					
Gender	0.813**	4.696***	-124	0.0782	457
	-413	-1654	-367	-457	-324
Gender*TLU	-0.0739	-0.326***	-0.0455	-0.0210	-0.0228
	(0.0451)	-118	(0.0447)	(0.0585)	(0.0283)
Age	0.00341	-0.00144	0.00268	-0.000466	-0.000825
	(0.00474)	(0.00561)	(0.00554)	(0.00528)	(0.00522)
Education	0.0510	0.0922	-0.00301	174	191
	-123	-148	-141	-141	-129
Family size	-0.0131	-0.0110	-0.000549	0.0110	-0.0495*
	(0.0254)	(0.0313)	(0.0336)	(0.0305)	(0.0265)
Rural Institutions					
Farmers Association	-108	0.0844	-167	0.0442	-104
	-142	-157	-162	-158	-149
Iddir	211	0.00833	-0.324**	0.0316	-185
	-161	-188	-163	-181	-160
Cooperative Union	-0.0873	-235			
	-140	-164			
Social Networks					
Total number of Relatives			0.00179	0.00507	-0.00560
			(0.00557)	(0.00611)	(0.00638)
Total number of Friends			-0.00580	-0.00454	0.00159
			(0.00402)	(0.00485)	(0.00429)
Resources and assets					
Total farm size	0.0257	0.00212	-0.0365	-0.0223	-0.0629***
	(0.0164)	(0.0181)	(0.0245)	(0.0220)	(0.0239)
Total TLU	0.0569	0.320***	0.0412	0.0186	0.0258
	(0.0450)	-118	(0.0448)	(0.0585)	(0.0283)
Total Asset Value			-0.00627**	7.81e-07	0.00366*
			(0.00291)	(0.00268)	(0.00213)
Non-food expenditure	-0.000860	-0.00705	0.0157***	0.00281	0.00119
	(0.00385)	(0.0103)	(0.00499)	(0.00388)	(0.00533)
Food expenditure	-0.0284	0.0134	-0.0102	0.0309	0.0108
	(0.0381)	(0.0475)	(0.0450)	(0.0460)	(0.0419)
Safety Net			192	-137	-241
			-270	-295	-293
Credit constrained	123	0.0698			
	-116	-137			
Access to Extension Services and Farmers Knowledge					
Took training on varieties	-252	-277			
	-208	-241			
Took training on pest and disease control	0.0933	0.0307			
	-138	-154			
Farmers Shock Experience and Expectation					
Pest and Crop Disease Frequency	0.119***	0.0431*	0.121***	0.173***	0.0482*
	(0.0241)	(0.0234)	(0.0278)	(0.0265)	(0.0259)
Future Pest and Crop Disease Expectation	0.442***	0.525***			
	-116	-141			
Constant	-1.992***	-5.903***	-0.994**	-1.855***	-1.044***
	-472	-1663	-438	-525	-395
Observations	613	613	613	613	613

counselling on climate change adaptation are more likely to engage in soil and water conservation practices and less likely engage in early planting for ex-ante drought

situations.

MVP results of all risk factors shows that farmers shock experience and expectation has a significant effect on their choice of both ex-ante and ex-post measures. Farmers in drought frequent areas are more likely to plant drought tolerant varieties and engage in soil and water conservation activities and less likely to apply early planting as ex-ante adaptation measures to prevent or minimize the adverse effects of drought. Farmers from drought frequent areas are more likely to engage in replanting and selling livestock which might contributed towards not using consumption reduction as an ex-post coping strategy to drought. Farmers from hailstorm frequent areas are more likely to choose replanting and selling livestock to cope in the aftershock and less likely to reduce their consumption. In pest and crop disease frequent areas farmers tend to plant pest tolerant varieties and diversify crops before its occurrence and sell livestock and assets aftershock. And, farmers with future pests and crop disease expectation are more likely to engage in crop diversification and planting pest tolerant varieties. Farmers who have high future drought expectation frequency tend to plant drought tolerant crops, drought tolerant varieties, early planting and engage in water and soil conservation as ex-ante drought preparation.

3.3.1 Complementary and substitute measures

Complementarity and substitutability of measures is analysed using LPCA and MVP and the results obtained from both methods are consistent. In addition to identifying dominant measures LPCA also shows which measures are complementary and which measures compete over the same resource. Figure 3.1 show score and loading plots of the first two principal components for all measures chosen ex-ante and ex-post in drought, hailstorm and pest and crop disease situations. Loading plots do not only indicate the major contributors they also show the correlation between measures in the matrix in general¹. This enables us to identify which measures are substitutes and which are complements. Measures clustered together have similar contribution in the matrix. The farther the strategy is from the origin in the loading plots, the higher its contribution to the total variation in the choice matrix. Selling livestock and selling non-livestock assets, for example, have high positive correlation in ex-post drought situation. If the farmer chooses one, the likelihood that the other will be chosen is higher. On the contrary, engaging in off-farm activities and out migration (rural-urban migration) go in opposite directions from selling livestock (or selling other assets) in the loading plot and are substitute measures. Same is true for replanting and reducing consumption. Planting drought tolerant crops and planting drought tolerant varieties are ex-ante complementary measures. Saving and engaging in off-farm activities are also complementary measures for drought. Early planting and crop diversification are complementary ex-ante measures for pests and crop disease.

¹MVP determines correlation between measures based on different farmer level characteristics, LPCA on the other hand, shows correlation between measures according to the total contribution to the variation in the choice matrix – is therefore more generic.

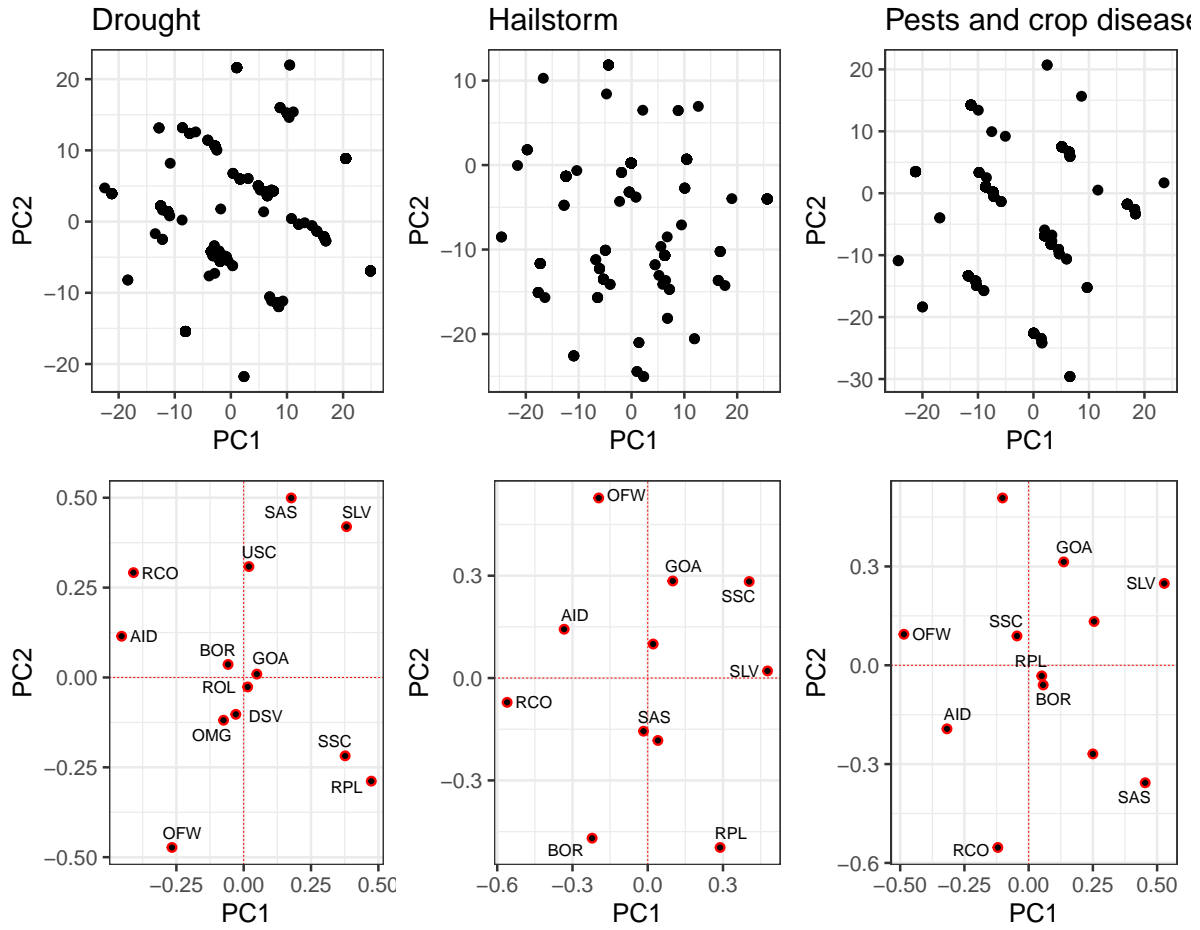


Figure 3.1: Ex-post Scores loading plots of LPCA

In MVP, on the other hand, complementarity and substitutability of measures is obtained from post estimation correlation matrix of the error terms of adoption equations. Table 3.10 shows most of the off-diagonal elements of the correlation matrix are statistically different from zero for all risk factors. This confirms that farmers choices of ex-ante as well as ex-post measures are interdependent and the application of an MVP model specification to the problem is appropriate.

Table 3.10: Correlation coefficient (rho) of MVP regression equations

Risk factor	<i>Correlation matrix</i>											
	Ex-ante						Ex-post					
	21	31	41	32	42	43	21	31	41	32	42	43
Drought	1.137*** (0.106)	0.601*** (0.0989)	0.494*** (0.1000)	0.777*** (0.0925)	0.753*** (0.109)	0.191** (0.0855)	0.219*** (0.0623)	0.208*** (0.0758)	-0.325*** (0.0668)	0.480*** (0.0731)	-0.0600 (0.0614)	-0.0325 (0.0740)
Hailstorm	21 0.624*** (0.133)	31 134 (0.0899)	32 0.811*** (0.182)				21 0.486*** (0.105)	31 -0.0552 (0.0945)	32 -0.0591 (0.0942)			
Pests	21 0.765*** (0.0989)						21 0.336*** (0.0810)	31 0.0227 (0.0870)	32 0.485*** (0.0846)			

Note:

Numbers in each column refers correlation between models mentioned in previous regression tables.

The result in Table 3.10 shows that there is complementarity and substitutability in farmers choices of ex-ante and ex-post measures for drought, hailstorm, and pests & crop disease. Planting drought tolerant crops and varieties, and soil and water conservation activities are used complementarily as an ex-ante adaptation options for drought. Farmers use selling livestock and selling other assets and replanting complementarily in response to drought. Farmers also have substitute ex-ante strategy measures for drought. The identified substitute measures are selling livestock and reducing consumption & replanting and reducing consumption. Farmers use increasing seed rate and engage in non-farm activities complementarily to reduce the outcome of hailstorm shocks.

On the other hand, replanting and selling livestock are complementary measures to cope with the aftershock. For pests and crop disease both before and after the occurrence measures are complementary than competitive. Planting pest tolerant varieties and crop diversification are complementary ex-ante measures while selling livestock, selling other assets and reducing consumption are complementary ex-post measures in response to pests and crop disease shocks.

3.3.2 Correlation between ex-ante and ex-post measures

LPCA is also used to see relationship between farmers choices of ex-ante and ex-post measures over the past ten years. Results show that farmers who planted trees as an ex-ante measure for drought are less likely to sell livestock and other assets after drought. Planting drought tolerant varieties and receiving aid are negatively correlated. The result also shows that ex-post measures have a strong contribution to the total variation in the choice matrix than ex-ante measures. This shows that farmers invest more on ex-post measures than ex-ante measures. For hailstorm off farm work and soil and water conservation are positively correlated to planting trees and stop sending children to school respectively. For pests and crop diseases, using pesticide is negatively correlated with planting pest tolerant varieties while engaging in off farm work is positively correlated with selling livestock. And, engaging in off farm work is negatively correlated with early planting and crop diversification. Figure 3.2 shows correlation between ex-ante and ex-post measures.

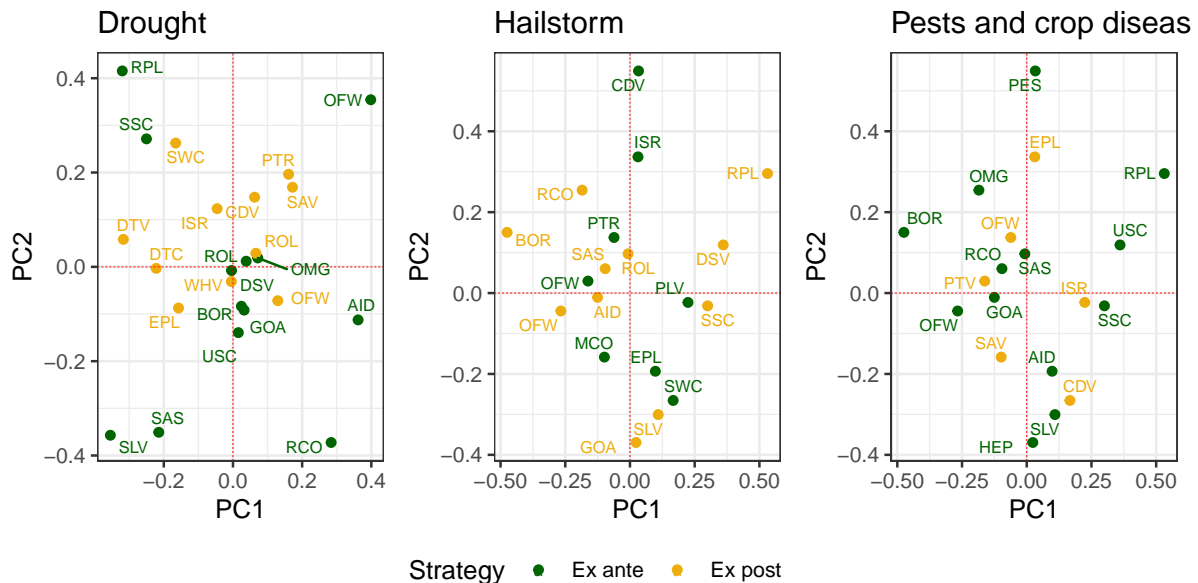


Figure 3.2: Ex-ante and ex-post measures: correlation

3.4 Feedback to agent based model

Some of the results obtained in the econometrics analysis are used as an input during parameterizing the farm decision model. Even though the sample used for econometric

analysis and agent based modeling in this thesis are different, the underlying principles of adaptation and mitigation of shocks is similar throughout Ethiopia. Besides the study area for the farm decision model is within the range of the study area used for the econometric analysis in this thesis. The main feedback from the econometric analysis to the farm decision model goes to the setting up of ex-ante planning by agents for shocks. The following are the main feedback from the results of the econometrics analysis used in the model in one way or another.

- Shocks: the most frequent and intense shocks identified in the econometrics analysis are included in the model to set-up agents' ex-ante planning measures
- Strategies: the strategies such as food storage, selling livestock, selling trees, for instance are included in the model in shock cases and as in the normal cases

Besides, econometric results help to shape our objectives in model calibration by establishing the standard ways the farmers behave when choosing measures.

Chapter 4

Validation of farm decision model

Chapter objectives

- *Showing validity of the farm decision model to do simulation experiments*
 - *Examining results of empirical model validation*
 - *Examining results of interactive model validation*
-

4.1 Structural model background and purpose

4.1.1 *Purpose*

This chapter presents validation results of the farm level mathematical programming model. The primary objective here is to show the quality of predictive accuracy of the model in contrast to the actual short-run production decisions made by farmers in the study area, given the underlying assumptions set in the model. Before validating the model, the underlying assumptions of validation and initialization of the model are explained. Later different versions of the model based on the agent's behavioral response towards risk to decide on the baseline model are compared. There are two different versions of the model where agents make ex-ante preparation for the possible occurrence of shocks or not. The model with these two settings is compared and chose the one with the highest resemblance to the survey data. Verification and validation results are presented after model selection.

4.1.2 *Underlying assumptions of model validation*

The basis of model validation resides in the assumptions set during model parametrization. The model assumes that farmers' short term production decisions can be predicted from the multi-agent farm level mathematical programming model if

the values of key parameters about farmers (described below) are known. Following are the underlying assumptions in the model:

- prices, wage rates, interest rates, inflation rates, discount rates, rotation constraints, yields, minimum energy and protein requirements, and cropping calendar are exogenous in the model
- farmers' expectations of yields and prices is known
- farmers take calculated risks only (they operate in a safe mode)
- farmers' asset endowments (land, labor and liquidity) are known at the beginning of the season before they make plans

4.2 Observations

4.2.1 *Initial endowments*

The initial endowments which are assumed to have a significant role in determining agent's short term production decisions are farm size, labor capacity, livestock and perennial ownership and capital in the form of cash¹. The average landholding in the agent population is 1.8 hectares ranging from 0.5 ha to 7 ha per household. To ease divisibility, plots were classified into areas of 0.125 ha and keep all growing activities as integer activities in the model.

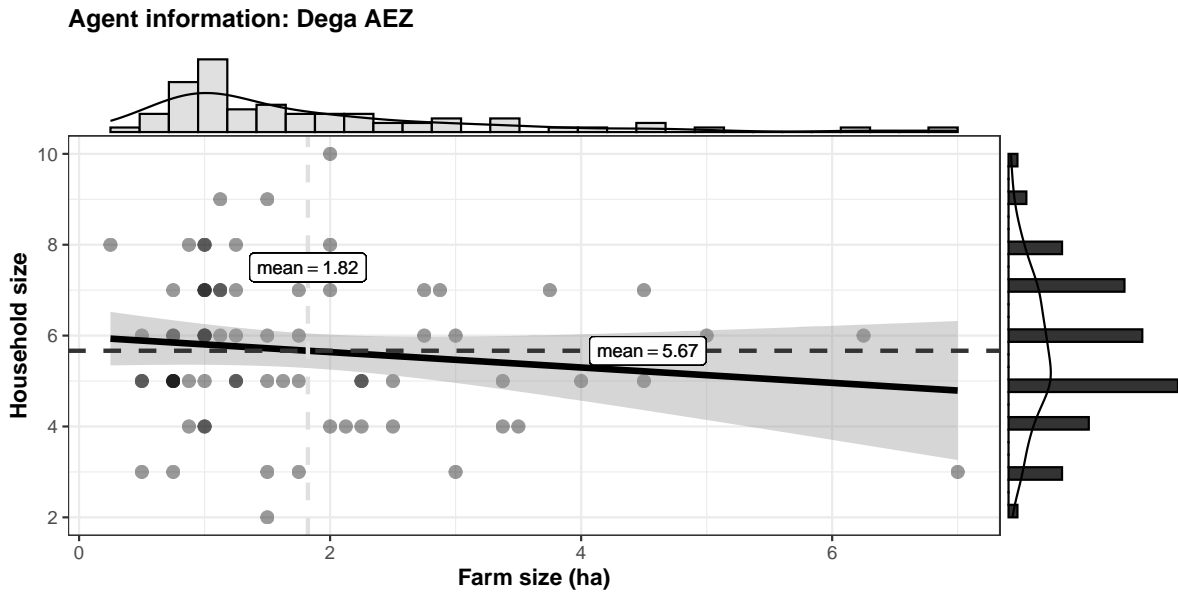


Figure 4.1: Agent information: correlation between household size and farmsize

Figure 4.1 shows that there is slightly negative correlation between farmsize and household size in the agent population.

¹Cash is relevant for financing farm operation costs at the beginning of the planning period before they collect their harvest.

4.2.2 Household composition

One of the most important agent information for the model's initialization is the households' labor capacity. Agents' labor capacity in the model is captured by the total number of different labor groups available. There are five labor groups in the model classified based on household members' age and gender (small child labor, child labor, male labor, female labor and senior labor). Age is dynamic in the model². To summarize the distribution of the different labor groups across agents by their material well being, agents were classified based on their farm size - often used as a proxy for smallholder farmers material well-being status in addition to livestock and labor capacity. The entire agent population is classified into three groups (better-off, average and worse-off farmers) based on quartiles of farm size in the sample.

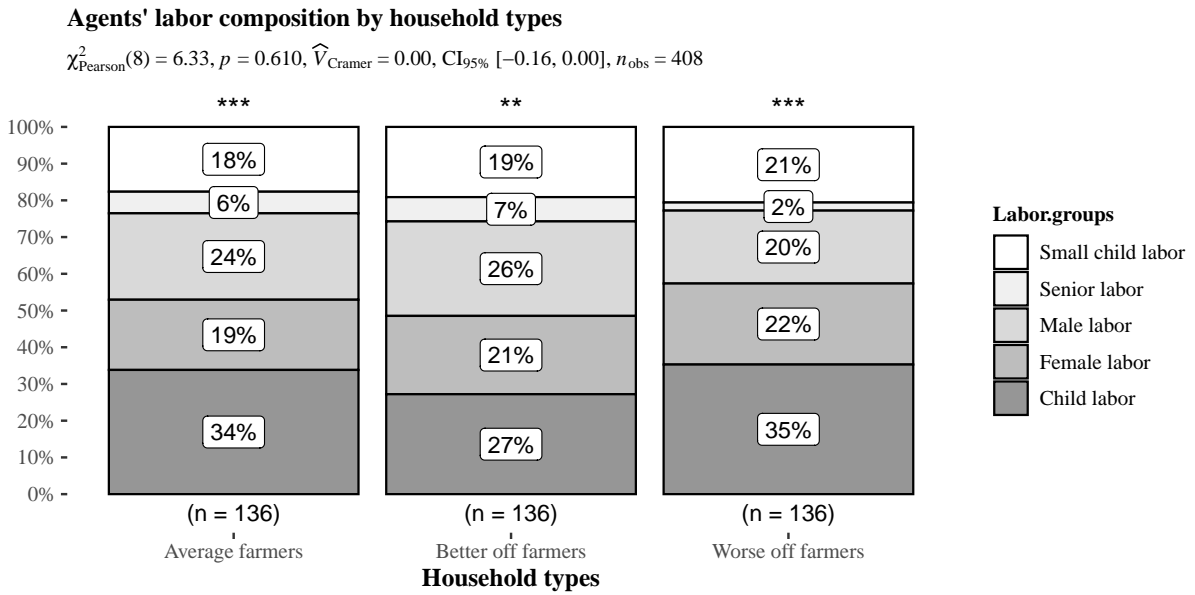


Figure 4.2: Agents' labor composition by household types

Figure 4.2 shows that child labor and small child labor constitute a substantial share of household members in the agent population on average. It depicts no significant difference between the distribution in the labor groups based on material wellbeing classification. In comparison, senior labor constitutes the smallest amount. This shows the population in the model is a young population, similar to the situation at the national level. The active labor force in the agent population is around 45% of the total agent population. These are the key participants in the major agricultural activities in the area.

²growth of household members and shift from one labor group to the next labor group based on age is captured across the planning horizon

4.2.3 *Exogenous variables in the model*

Time series data on prices and yield of crops are obtained from the Central Statistical Agency of Ethiopia database (CSA 2019). Data on minimum energy and protein requirements of household members by their corresponding age is obtained from FAO database (FAO 2001). Constant expectation is assumed in the model. The cropping calendar (land preparation, sowing dates, weeding, harvesting and threshing periods) of major crops in the area are exogenous. Data on the cropping calendar used in the model is obtained from empirical literature, focus group discussions and key informant interviews (USDA 2018). The cropping calendar is typical of the Dega AEZ. Agents also have the option of double cropping (barley after potatoes). The cropping calendar is for the main rainy season (*kiremt* or *meher*).

4.3 Empirical validation

4.3.1 *Benchmarks for model validation*

Benchmarks are a set of locally stylized facts that characterize a farming system and a typical farmer's behavior in that farming system. The basis for model validation and the underlying assumptions are these benchmarks that characterize the farming system modeled. The benchmarks could be considered well-established knowledge or facts, customized rules of farm operations, strong and consistent input-output relationships that characterize farmers and the farming system the model is trying to simulate (Christian Troost 2014). The main sources to establish benchmarks are survey data, KIIs, FGDs, secondary data, and literature. These benchmarks are then used as the basis to design our validation experiment. Benchmarks were set on farmers' main characteristics related to their land-use decisions in crop and tree production and livestock production. The following sections summarize the available systematic relationships in farmers' land-use decisions and their livestock production.

4.3.2 *Crop and woodlot tree production*

Figure 4.3 shows the distributions of observed land-use by farmers in the sample for all crops grown. Potatoes and acacia woodlot tree plantations have the highest land-use coverage in hectares, followed by barley, teff and wheat. Potatoes are the most grown crop in the area. This is attributed to the suitability of acidic soils for potato production. In addition to potatoes, acacia decurrens and teff are the most widely grown crops among farmers in the sample. This is perhaps related to the high intercropping rate of acacia decurrens with teff in the first year. Most farmers in the sample allot a piece of land for the major crops in general. However, relatively larger farm size is allocated for acacia and potatoes.

Observed land-use

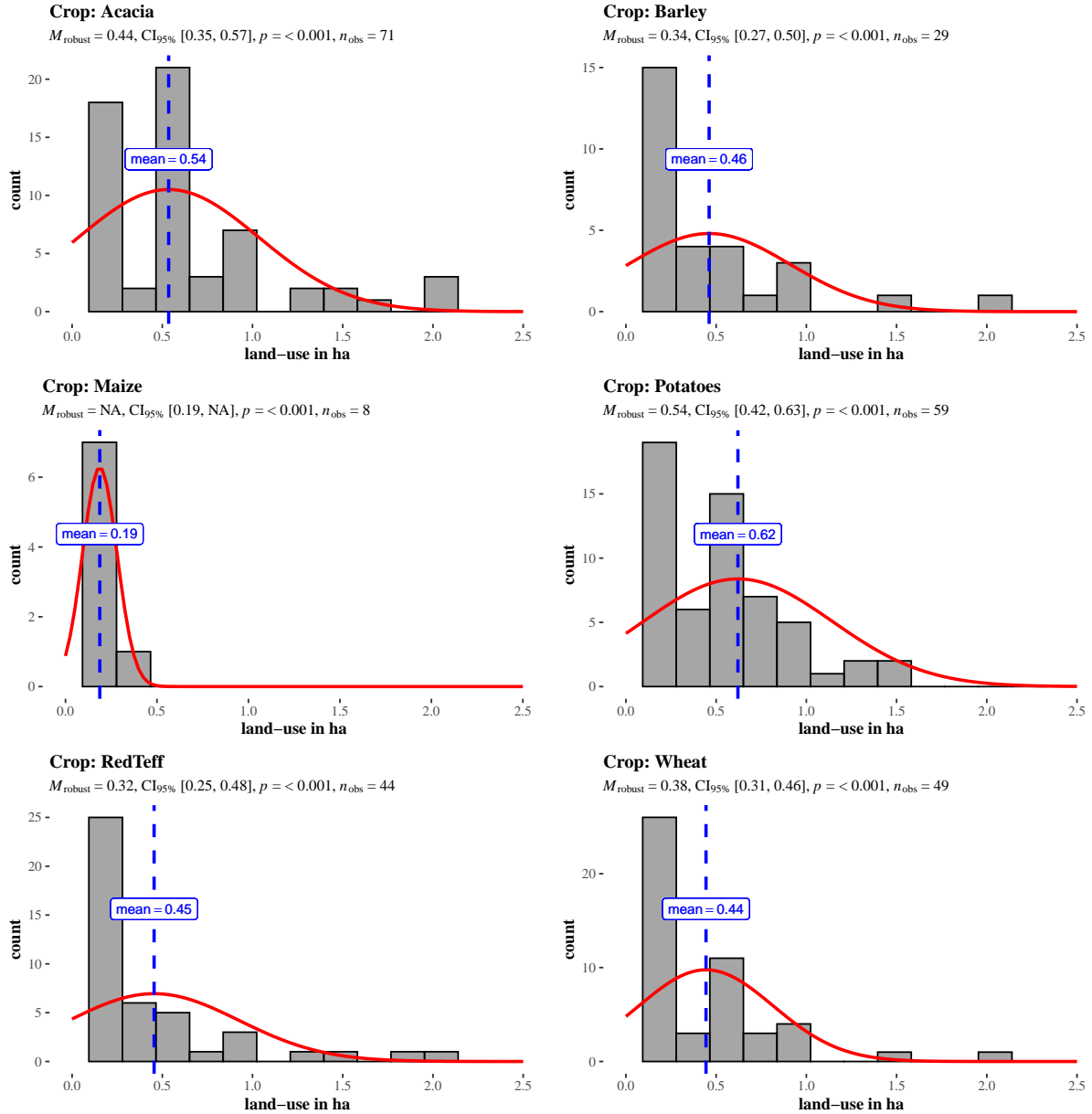


Figure 4.3: Distribution of land-use

To see the heterogeneity of land allocation, the land-use share distribution of each farmer in the sample for all the growing crops is plotted. The box plots in Figure 4.4 show, on average, farmers in the sample allocate a larger share of their respective farmland, followed by wheat and teff. On average, each farmer allocates 31% and 28% of their total farm size to potatoes and acacia decurrens.

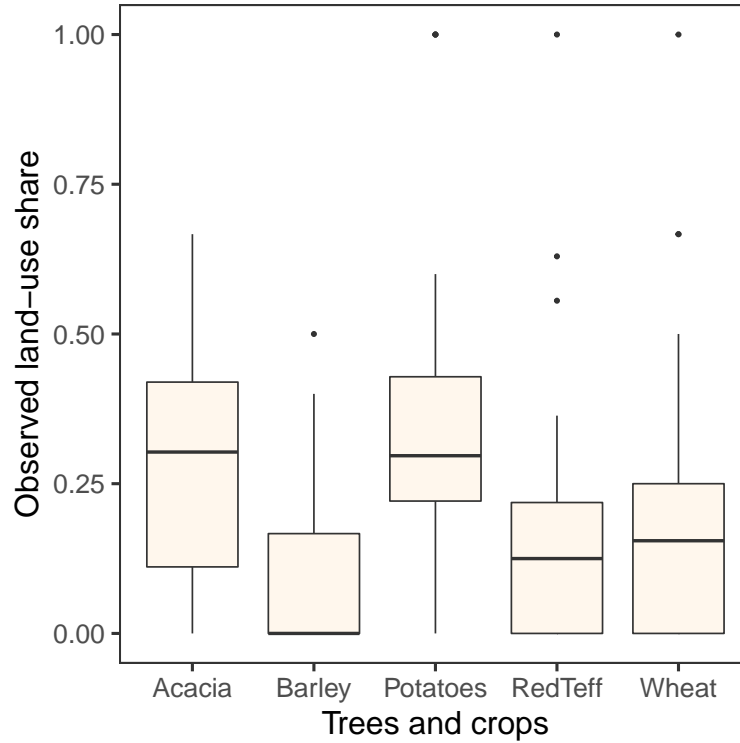


Figure 4.4: Distribution of land-use share in the study area

Furthermore, the study applied descriptive and statistical techniques to examine a systematic relationship between farmers' endowments and the amount of land allocated for a particular crop. First, distributions of farmers' endowments are plotted and compared the results for growers with the non-growers. The aim is to examine why some farmers are growing a particular crop and others not. The results are presented in figures 7.1 to 7.15. From the shapes of the distributions, it can be understood that land-use decisions on crops and perennials are driven by endowments (mainly land and livestock), where there is a noticeable difference on asset endowments of growers and non-growers. Figures are shown in Appendix C

Furthermore, to examine the determinants of farmers' discrete land-use decisions, a dummy variable on growers of each crop is regressed on household and community-level characteristics. Table 4.1 and Table 4.2 show logistic regression results and the corresponding odds ratio of explanatory variables. The results show that, farm size, livestock ownership (TLU) and information on prices significantly affect the choice to grow a particular crop in the study area.

Table 4.1: Logistic Regression of land-use Decisions

	1 = grow, 0 = don't grow				
	acacia	barley	potatoes	redteff	wheat
	(1)	(2)	(3)	(4)	(5)
hhsiz	.45 (1.32)	.15 (.77)	−.37 (.83)	.94 (.74)	−.14 (.60)
farmsiz	2.27* (1.17)	.02 (.25)	−.30 (.25)	.25 (.24)	.36 (.31)
Small.child.labor	−.26 (1.28)	−.83 (.74)	−.05 (.71)	−1.25* (.69)	.71 (.57)
Child.labor	−.38 (1.44)	−.77 (.82)	.55 (.81)	−.39 (.73)	.35 (.61)
Male.labor	1.89 (1.46)	.12 (.86)	.87 (1.00)	−.91 (.88)	.13 (.66)
Female.labor	−.75 (1.18)	1.23* (.74)	.12 (.85)	.06 (.66)	−.81 (.55)
TLU	−.34 (.23)	.26 (.16)	.03 (.18)	−.03 (.15)	−.04 (.15)
Access.to.credit.to.buy.seed	.06 (1.44)	1.43* (.86)	−.61 (.88)	−.12 (.81)	−.05 (.81)
Fertilizer.price	.35 (1.49)	−.99 (.98)	−2.44* (1.45)	−.91 (.88)	.71 (.79)
Input.market.information	2.54 (1.69)	1.99** (.93)	1.09 (1.07)	1.28 (.85)	−.07 (.77)
Labour.wages	.23 (1.74)	−3.25** (1.43)	.33 (1.27)	−.22 (.92)	−.31 (.93)
Output.price	1.87 (1.59)	−2.16** (1.06)	.01 (1.07)	−.39 (.89)	−.23 (.87)
Seed.price	−2.24 (2.62)	−.37 (1.19)	1.12 (1.41)	1.40 (1.19)	.18 (1.02)
Seed.quality	−1.42 (1.93)	1.37 (1.15)	−2.25 (1.38)	−2.95** (1.15)	.17 (.96)
Timely.seed.supply	−1.15 (1.86)	1.26 (1.02)	.97 (1.10)	.35 (.92)	−.60 (.93)
Constant	−2.00 (2.37)	−2.02 (1.71)	3.73* (2.04)	−.77 (1.44)	.51 (1.37)
Observations	72	72	72	72	72
Log Likelihood	−18.53	−33.51	−26.85	−36.93	−38.34
Akaike Inf. Crit.	69.05	99.02	85.70	105.87	108.67

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 4.2: Logistic Regression of land-use Decisions - ODDS RATIOS

	1 = grow, 0 = don't grow				
	acacia	barley	potatoes	redteff	wheat
	(1)	(2)	(3)	(4)	(5)
hhsz	1.57 (1.32)	1.16 (.77)	.69 (.83)	2.55*** (.74)	.87 (.60)
farmsize	9.69*** (1.17)	1.02*** (.25)	.74*** (.25)	1.28*** (.24)	1.43*** (.31)
Small.child.labor	.77 (1.28)	.44 (.74)	.95 (.71)	.29 (.69)	2.03*** (.57)
Child.labor	.69 (1.44)	.46 (.82)	1.72** (.81)	.68 (.73)	1.41** (.61)
Male.labor	6.64*** (1.46)	1.13 (.86)	2.39** (1.00)	.40 (.88)	1.14* (.66)
Female.labor	.47 (1.18)	3.42*** (.74)	1.13 (.85)	1.06 (.66)	.44 (.55)
TLU	.71*** (.23)	1.29*** (.16)	1.03*** (.18)	.97*** (.15)	.96*** (.15)
Access.to.credit.to.buy.seed	1.06 (1.44)	4.20*** (.86)	.54 (.88)	.88 (.81)	.95 (.81)
Fertilizer.price	1.42 (1.49)	.37 (.98)	.09 (1.45)	.40 (.88)	2.03*** (.79)
Input.market.information	12.67*** (1.69)	7.32*** (.93)	2.98*** (1.07)	3.60*** (.85)	.94 (.77)
Labour.wages	1.26 (1.74)	.04 (1.43)	1.39 (1.27)	.80 (.92)	.73 (.93)
Output.price	6.50*** (1.59)	.12 (1.06)	1.01 (1.07)	.68 (.89)	.79 (.87)
Seed.price	.11 (2.62)	.69 (1.19)	3.05** (1.41)	4.06*** (1.19)	1.19 (1.02)
Seed.quality	.24 (1.93)	3.95*** (1.15)	.11 (1.38)	.05 (1.15)	1.19 (.96)
Timely.seed.supply	.32 (1.86)	3.54*** (1.02)	2.63** (1.10)	1.42 (.92)	.55 (.93)
Constant	.13 (2.37)	.13 (1.71)	41.84*** (2.04)	.46 (1.44)	1.66 (1.37)
Observations	72	72	72	72	72
Log Likelihood	-18.53	-33.51	-26.85	-36.93	-38.34
Akaike Inf. Crit.	69.05	99.02	85.70	105.87	108.67

Note:

*p<0.1; **p<0.05; ***p<0.01

4.4 Empirical validation results

To empirically validate the model simulated and observed values of land-use and livestock production were compared on a one to one basis. Accordingly, land-use values and shares of each crop for all farmers in the sample are fitted using multinomial logit regression. The fitted values from the regression are compared with the farmers' actual land-use decisions in the survey and simulated³ land-use decisions by agents in the model. Scatter plots of fitted, observed and simulated land-use values are plotted over farm size to see the consistency of fitted and simulated results with the observed results. Figures 4.5 and 4.6 show scatter plots of land-use and land-use share to total farm size.

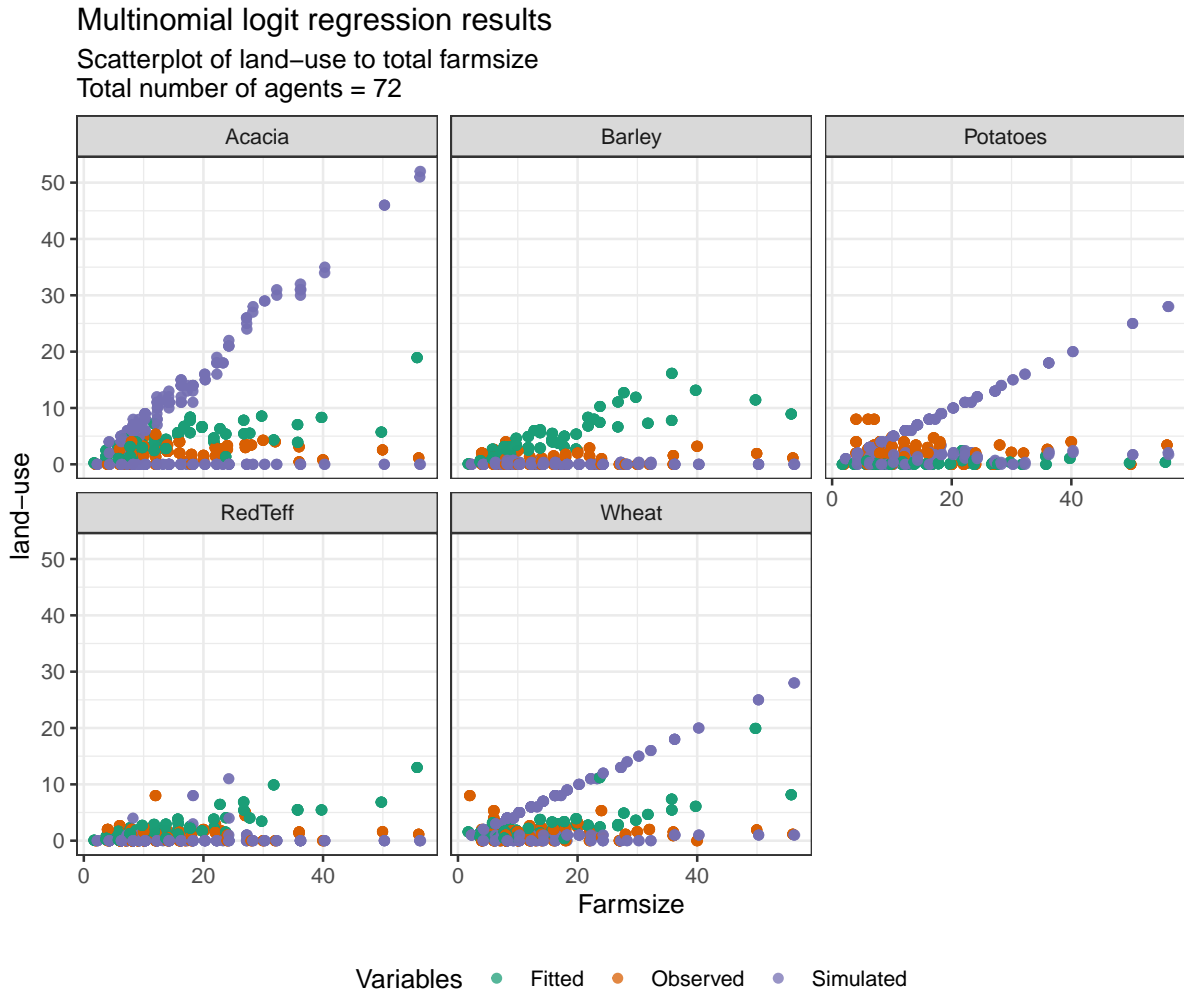


Figure 4.5: Land-use: observed vs simulated land-use in pixels of 0.125 ha

The results from both figures show that the model has higher predictive power for small farm size farmers. As the farm size increase, the model tends to overestimate land-use-values. This is persistent for acacia decurrens, potatoes and wheat. Besides,

³The baseline scenario at the first simulation period is used for comparison

in terms of land-use shares, the model overestimates values compared to observed and fitted values. Results using farm size are compared following its significant contribution to land-use decisions as per the logistic regression results above.

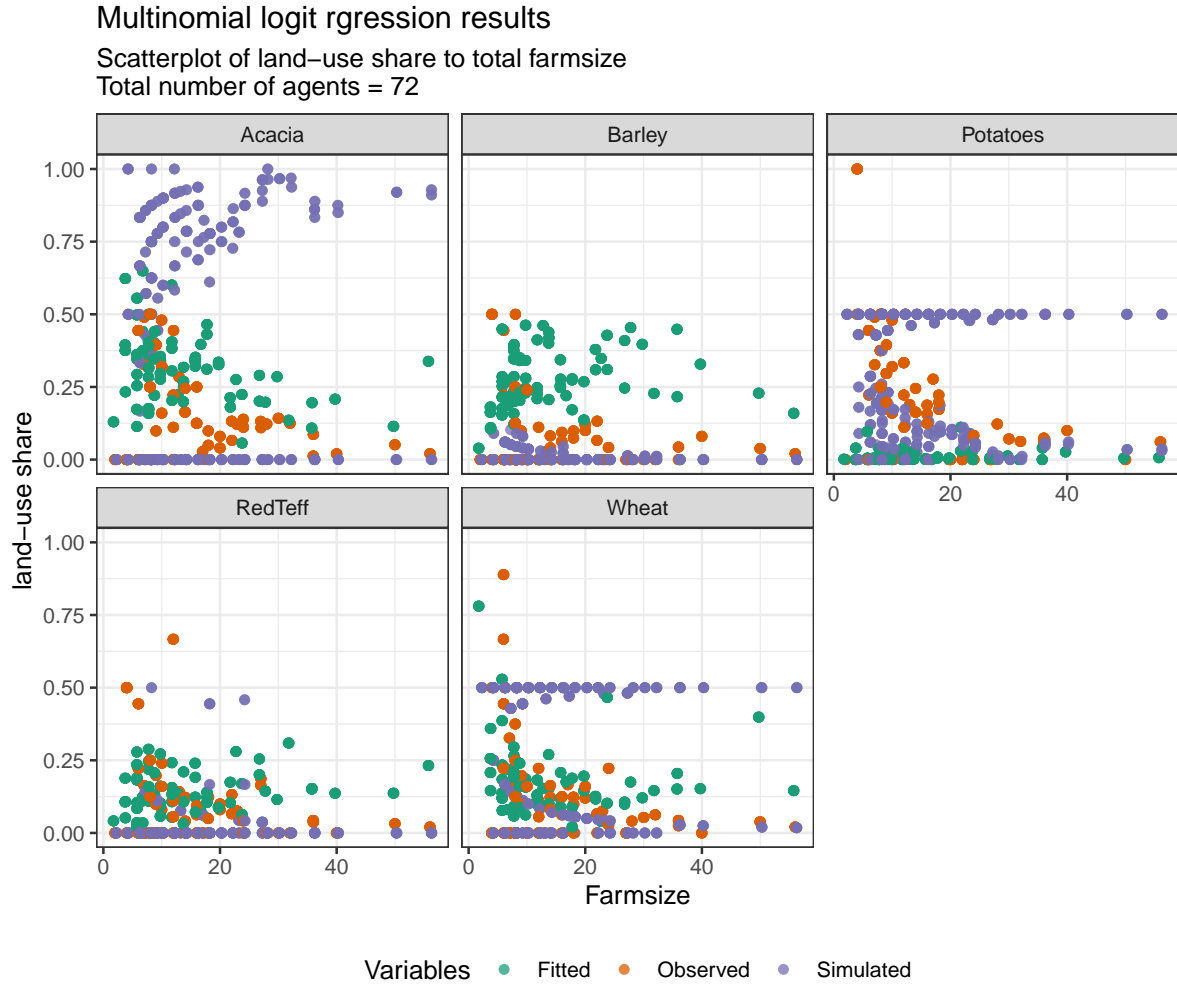


Figure 4.6: Land-use shares: observed vs simulated land-use shares in pixels of 0.125 ha

Furthermore, since potatoes and acacia are the most commonly grown crop/tree in the area, simulated land-use results of agents in the model are compared with farmers' actual land-use decisions on a one to one basis. The results are presented in Figure 4.7. The 45-degree line is used as a reference for the predictive capacity of the model. The results show that the model underestimates land-use decisions of acacia decurrens in the area in the baseline scenario with no shock and with ex-ante planning. The results are better for potatoes. The prediction of the model is more accurate in the initial years of simulation.

Acacia Dicurrens potatoes

Simulation Period
2018 – 2021

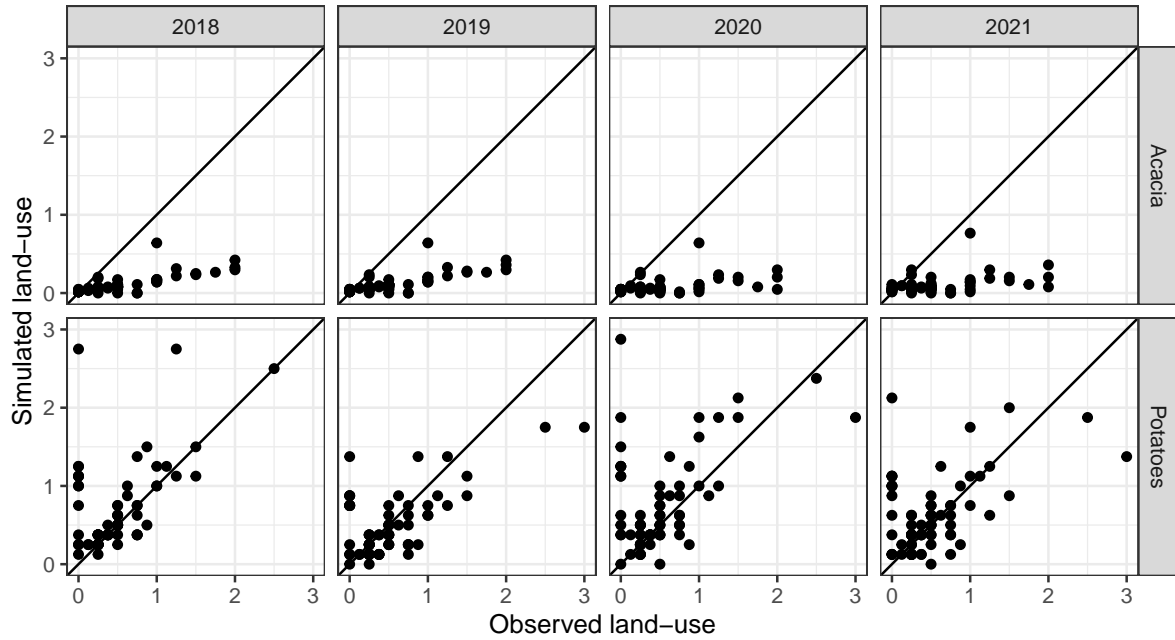


Figure 4.7: Simulated versus observed values of acacia and potatoes in the baseline scenario

4.4.1 *Conclusions from empirical validation results*

- Potatoes and acacia have highest land-use shares followed by wheat, teff and barley which is in line with the values obtained in the model
- Farmer endowments mainly land and livestock ownership determine their choice of crops/trees to grow
- The model has better predictive power for land-use shares of small farm size farmers - mainly for acacia, potatoes and wheat. As farmsize increases the model overestimates land-use shares
- Model prediction is better in the initial simulation years.

4.5 Interactive model validation

4.5.1 R shiny apps user interface (UI)

Interactive model validation is not new in agent-based modeling using MPMAS. Mössinger, Troost, and Berger (2022) showed how interactive model validation help improve the analysis of agricultural systems using MPMAS. For this study two Shiny apps were developed for interactive model validation sessions. The first is the

Online Expert Feedback Survey⁴. All validation and verification related questions for experts are included in this app. There are four sets of questions - background information about the expert; Turing test questions; verification/validation questions; and questions on the interactive tool's overall feedback. The Turing test questions are stand-alone questions where all the relevant information to answer the questions is provided on the spot. In contrast, answering the verification and validation questions requires referring to the second (main) interactive model validation app.

The online feedback survey app is synchronized to dropbox cloud storage and the data is stored in the cloud upon each submission. This enabled us to get the data in real-time. The app is developed in such a way that it will be self-explanatory. The necessary steps to follow and tasks to do are described inside. Video tutorials are also included for further clarification. The app is developed in two languages - English and Amharic. This is primarily to smooth communication between experts and the app as much as possible. Every expert feedback survey session was guided by the researcher and was conducted via zoom video conferencing. This created smooth sessions in terms of communication and clarity. All video discussions in the zoom sessions are recorded. Much of the feedback about the model is found in the discussions than the recorded answers from the structured questions.

Figure 4.8: Online expert feedback survey web app user interface

⁴The Online Expert Feedback Survey web app is deployed to the link address https://mpmas-ethioacacia-mpv.shinyapps.io/expertfeedback_english/

The second Shiny app is the main interactive model validation app⁵. This is basically a simple representation of the farm decision model. Three agents with low, average and high endowments from the 72 agents in the model were selected and presented all model validation outcomes for these agents throughout. The selection of these three farmers was based on farm size, labor capacity and quality and livestock ownership. The purpose of having three agents instead of one is to see the model's performance for agents with different resource settings. The main app is also presented both in English and Amharic versions. Besides, each step and action is explained on the app for easy navigation. The baseline scenario represented in the model is the WAN scenario where agents can plan with *Acacia Decurrens* (W), with ex-ante planning (A) and no-drought (N).

Figure 4.9: Main interactive model validation web app user interface

⁵The main interactive model validation web app is deployed to the link address https://mpmas-ethioacacia-mpv.shinvapps.io/rshiny_english/

percentage changes in these parameters. Slider bars are used to select the values of these parameters. In this way, experts were able to select different values and combinations of the parameters of interest and see the model’s corresponding simulated results. Experts need to refer to this main app to answer verification and validation questions in the online expert feedback survey. For each question, a specific tuning and setting of these parameters are provided before questions are asked. After experts changed parameter values on the slider bar as requested, they reran the model (by clicking the run button) to get the updated results in the output panel - which is the last portion of the interface.

The main interactive model application’s output panel shows a graphical representation of outcome variables from the model after each run. These outcome variables are directly linked to the verification and validation questions. The outcome variables are land-use decisions, type and number of livestock kept, total sales revenue from all sources, revenue from crops, revenue from tree perennial products and revenue from off-farm employment. Each design point is run for 4 simulation periods starting from the year of data collection (2018-2021) and for 15 years planning horizon.

4.5.2 Settings and tuning

The parameter selection for tuning in the Shiny app is based on the study area’s context, the sensitivity (elasticity) of outcomes towards changes in the parameter, and the relevant research question the study tries to answer. That is why exogenous variables are used, mainly prices and off-farm capacity of agents in the model, as tuning parameters.

4.5.3 Sample of Experts

Before the actual interactive session, a pretest had been done using experts from University of Hohenheim to check contents and functionality of the apps. A total of 10 experts participated in the actual interactive session. The selection of sample experts was purposive. Experts who have been researching in the study area, with the relevant expertise to the study and adequate experience are selected. Nine experts are researchers from Amhara Regional Agricultural Research Institute (ARARI), and one is from Adet Agricultural Research Center.

Table 4.3: Characteristics of experts in the sample

id	Name	Expertise	Institute	Education	Experience years
1	Birhanu Endalew	Soil science	ARARI	Masters	17
2	Yalfal Temesgen	Agricultural Economics	ARARI	Masters	8
3	Beyene Belay	Forestry	ARARI	PhD	15
4	Daniel Woldegiorgis	Rural development	ARARI	Masters	19
5	Melkamu Elmiyhun	Plant breeder	ARARI	Masters	13
6	Yazie Chanie	Agricultural Economics	ARARI	Masters	18
7	Walelign Zegeye	Plant pathology	ARARI	Masters	29
8	Molla Mekonen	Plant breeder	ARARI	Masters	26
9	Amsalu Nigatu	Forestry	ARARI	Masters	8
10	Atinkut Fentahun	Plant breeding	Adet ARC	Masters	13

Experts from various fields in agriculture are included in the sample. The sample includes agricultural economists (2), forest researchers (2), plant breeders (3), rural development and extension expert (1), soil scientist (1) and plant pathologist (1). The minimum level of education attained in the sample is masters and the maximum is Ph.D. Experts in the sample have adequate experience in their respective fields. The average years of experience in the sample is 16.6 years, ranging from 8 to 29 years.

4.5.4 Turing test results

Following the methodology applied in Christian Troost (2014), the first part of the interactive model validation session is the Turing test. The Turing test aims to test the plausibility of the results from the farm decision model. There are five farmer types (Farmer type 1 - Farmer type 5) provided for the Turing test - large farm-sized farmers, high labor capacity farmer, farmer with the largest livestock ownership, and relatively better off and worse off farmers in the sample in general. The primary objective of the classification is to see the predictive performance of the model for farmers in different resource settings and to ensure representativeness thereof. The profile⁶ of each farmer type is given at the beginning of each Turing test question.

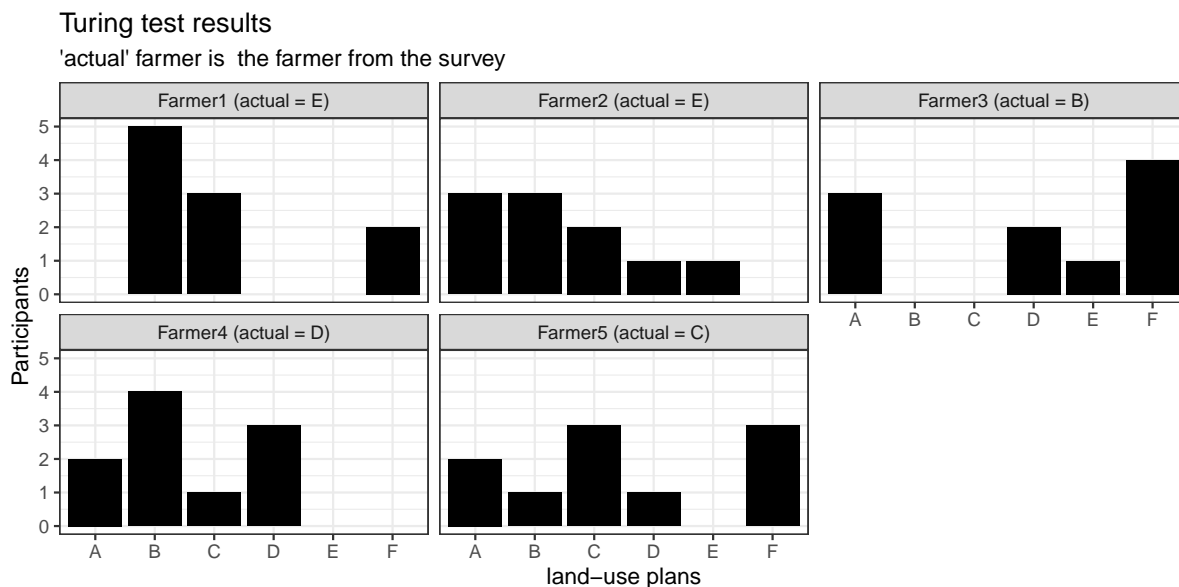


Figure 4.10: Turing test results

For each farmer type, the model was run with several parameter combinations and the major land-use decisions (plans) of six alternative farmers/agents are given. One of which is from survey data, and the rest five are simulated results from the model. For each Turing test question, experts compare the results and choose one of the six options they thought is an actual farmer from the survey.

⁶Profiling is based on family size, farm size and livestock ownership

As shown in Figure 4.10, most of the experts' choices (86%) about land-use plans of the actual farmer from the survey are incorrect. They chose land-use plans of agents obtained from simulated results. Only 7 out of 50 choices were correctly specified towards the actual farmer. At least three options have been chosen for each farmer type, whereas in most cases, four and five options out of six options are chosen. For two farm types, all experts chose agents' simulation results only. Only in one of the farmer types were the actual farmer chosen by three out of ten experts.

4.5.5 Results of verification and validation experiments

The second section of the interactive model validation session includes validation and verification experiments. The purpose of the verification and validation experiments is to attest to the model's plausibility and predictive accuracy. The verification questions are based on two experiment settings. The first is experiments on the baseline scenario. In this setting, all the parameter values in the model remain unchanged. Therefore, experts were asked questions to verify the plausibility of the model's results in its baseline state. Six of the total of eleven verification and validation questions are on these baseline settings of the model. On the app, experts were able to see graphs on model output for each question asked.

Based on experts, most of the results obtain in the baseline are realistic (60% to 90%) except on the results from livestock where almost all of the experts said that it is not realistic. Most experts also argued that the baseline model should not be dominated by bamboo, it should be acacia dicurrense. They said that is what is happening in the study area at the moment. Equines were not included in the baseline model. And, almost all experts have commented that equines are missing and have to be included. Horses are main source of draft power in the area. Horses also serve as a means of transportation. In addition to the economic benefits, horses has a social value in the community and should be included thereof.

Most of the experts said that the ten percent assumption on labor availability is plausible. Some of them said it could even be more than 10%. However, according to experts, better-off farmers are net buyers of labor (not realistic for better off and realistic for the rest). Because of low agricultural productivity, before acacia, there has been an extensive migration of labor from the study area to more productive lowland areas, mainly in the harvesting season. They migrate to harvest maize, cotton and sesame in large public and private farms in Jawi, Ayo, Quara, Metema, Humera, Soma, Pawe and several other places. The emergence of acacia in the area has created a lot of job opportunities. There are off-farm activities in acacia seedling preparation, charcoal making, pruning and preparation of logs, transportation of logs, making bamboo products, loading, transporting charcoal, cutting trees. The average daily wage rate ranges from 70 to 120 ETB per day.

Details on experts remarks on the baseline experiment is provide in Table 4.4 and Table 4.5.

Table 4.4: Verification experiment results: (Experiment = Baseline)

<i>Settings: Everything remains unchanged and off-farm labour availability remains at 10%</i>						
Expert id	Verification / Validation questions					
	In the baseline farmers grow annual crops with bamboo universally, do you think farmers' land use decisions are realistic?	In the baseline farmers keep only chicken and cows, do you think it is realistic?	In the baseline farmers get higher proportion of their sales revenue from tree products, do you think it is realistic?	In the baseline farmers get higher sales revenue from potatoes among crops, do you think it is realistic?	In the baseline farmers get higher sales revenue from tree products, do you think it is realistic?	In the baseline if farmers were only able to work 10% of their excess labor off-farm they will get up to 16, 000 ETB, do you think it is realistic?
1	Not realistic	Not realistic	Realistic	Realistic	Realistic	Not realistic
2	Realistic	Not realistic	Realistic	Not realistic	Realistic	Realistic
3	Not realistic	Not realistic	Realistic	Realistic	Realistic	Realistic
4	Realistic	Not realistic	Realistic	Realistic	Realistic	I don't know
5	Realistic	Not realistic	Realistic	Realistic	Realistic	Realistic
6	Realistic	Not realistic	Realistic	Realistic	Realistic	Realistic
7	Realistic	Realistic	Realistic	Realistic	Realistic	Realistic
8	Not realistic	Not realistic	Realistic	Realistic	Realistic	Realistic
9	Not realistic	Not realistic	Realistic	Realistic	Realistic	Realistic
10	Realistic	Not realistic	Not realistic	Realistic	Not realistic	Realistic

The second experiment setting asks questions based on the future (long run) price variability and off-farm work availability changes. Attributed to heavy rain, the acidic content of the soil in the study area is very high. As a result, crop productivity is very low. This was one of the driving factors for expanding Acacia woodlot plantations in the area in the past decade. Compared to crops, the income farmers get from acacia is very high. Besides, acacia is a leguminous tree that fixes nitrogen into the soil. Which eventually reduces soil acidity, soil erosion, and recovers the soil fertility. These multifaceted benefits led to the extensive and fast conversion of croplands into acacia woodlots.

However, during the 2018 survey, farmers in FGDs mentioned that price fluctuation is the main threat to acacia production in the area. In the interactive session, it has also been established that prices have decreased at the farm gate and are distorted by brokers and traders. On the contrary, soil fertility has been improving because of repeated cycles of acacia plantations. Moreover, the price of crops has constantly been increasing for several years in Ethiopia in general. One of this study's objectives is to see if farmers would go back to annual crops in these push and pull factors. And, all the questions in this section are asked, considering this development.

The questions are asked in an investigative manner:

- a 50% decrease in bamboo price, keeping other variables constant and observing agents' land-use plans.
- a decrease acacia charcoal and bamboo culm price by 50% simultaneously, keeping everything unchanged and observed land-use plans.
- Keeping the prices of tree products unchanged, an increase all crops' prices by 50% and observed results.
- a simultaneously decreased the price of tree products by 50% and increased the crops' prices by 50% and observed agents' land-use decisions.

With future price variability, most of the results from the model are considered as a good fit to the reality by experts. The model was considered as a good representation of agricultural practices in the area with 67.5% (27 out of 40) responses from experts on verification and validation questions as "good fit."

Table 4.6 and Table 4.7 show results from the verification and validation questions from the interactive session.

Table 4.5: Verification experiment results: (Experiment = Future price variability)

<i>Settings: Changes in future prices and capacity of off farm labor availability</i>					
Expert id	Verification / Validation questions				
	Suppose the price of bamboo culm decreases by 50%, keeping other parameters constant. Do you think the shift in land use from bamboo to acacia is a good fit?	Suppose the price of bamboo culm and acacia charcoal price decreases by 50% simultaneously, keeping other parameters constant. Do you think the shift in land use from trees to crops is a good fit?	Suppose the price of crops increases by 50% simultaneously, keeping other parameters constant. As a result, there is no significant change in land use. Do you think it is a good fit?	Suppose the price of crops increases by 50% and price of charcoal and bamboo culms decrease by 50% simultaneously, keeping other parameters constant. Do you think the shift in land use from trees to crops is a good fit?	Suppose off farm capacity increases from 10% to 25% and then to 50%. Which one of these capacities do you think is a good fit?
1	Good fit	Good fit	Good fit	Good fit	None
2	Overestimated	Overestimated	Good fit	Overestimated	None
3	Overestimated	Good fit	Good fit	Good fit	None
4	Good fit	Overestimated	Good fit	Good fit	10%
5	Good fit	Good fit	I don't know	Good fit	10%
6	Good fit	Overestimated	Good fit	Good fit	25%
7	Good fit	Overestimated	Good fit	Overestimated	10%
8	Overestimated	Overestimated	Good fit	Good fit	None
9	Good fit	Overestimated	Good fit	Good fit	None
10	Overestimated	Good fit	Good fit	Good fit	10%

Another challenge during model parametrization was determining the availability of off farm work for agents in the model. Using the model it is possible to know the amount of excess labour after optimization. But how much can they work is not known. Agents can also work in off farm activities in the model but were only allowed to work 10% of the excess labor they have. This is because of no data on off farm availability in the area. As a result, experts were asked about the availability of off farm labor in the area. This is covered by two questions in the interactive validation.

4.5.6 *Conclusions from interactive validation results*

- Turing test results show that the model predicts land-use decisions accurately in 4 from 5 cases
- The land-use share of bamboo in the baseline scenario is overestimated
- Equines have to be included in the model
- Higher sales revenue obtained from tree products and livestock is realistic
- Most experts agreed that 10% assumption of the off-farm labor availability as a percentage of excess labor in the household is realistic.
- Soil fertility is an essential factor in addition to prices to drive farmers to shift from crops to trees and vice versa

4.6 Corrections to the model after model validation

Based on the results obtained in model validation the following features are improved in the model before the final simulation runs were done.

- Equines were added as one of the livestock production options
- Planting bamboo is only limited to farmsteads
- Acacia seedling disease is introduced as shock based on information obtained from the interactive model validation

Chapter 5

Farmers' ex-ante planning for shocks and the role of small scale agro forestry

Chapter objectives

- *Examining the effects of shocks on agents' income and the role of ex-ante planning for shocks*
 - *Examining the income effect of agents' investment in acacia dicurrens*
 - *Examining the effect of long-run price variability on agents' income*
 - *Disentangling the role of household specific endowments on income*
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This chapter presents results obtained from simulation experiments of the farm decision model. The validation results shown in the previous chapter provide a basis to do simulation experiments using the model and draw sensible conclusions about the agent population comparable to what is happening in reality with farmers. The missing or incorrect model features pointed out by experts in the interactive model validation are incorporated in the model before the final simulation experiments were run.

The simulation results are presented in two subsections. The rationale and design of each simulation experiment are explained before the results are shown. First, the contribution of acacia to livelihoods is examined. Accordingly, the effect of investment in acacia on income and land use is examined, followed by an analysis of the effects of shocks on income and the role of ex-ante planning by agents in curbing the adverse effects of shocks. Model convergence in repeated samples is presented in the first subsection. Second, analysis of the sustainability of acacia is presented by examining agents' response to expected price shocks in the long run. For each subsection, the aggregated results summarizing values at the agent population level are presented first, followed by disaggregated results to disentangle household-specific drivers that

determine the direction and/or intensity of effects on the outcome variable. All the results presented are summarized over sample repetitions from the uncertainty analysis.

5.1 Contribution of acacia on agents' livelihood

Rationale

Expansion of acacia-based small-scale agroforestry in the past decade has brought both economic and ecological benefits for smallholders in the study area (Nigussie et al. 2017 ; Berihun et al. 2019). This study focuses only on the economic aspect of investment in acacia and aims at quantifying the economic (financial) benefits from investment in acacia for smallholder farmers. Researches so far have used tools such as NPV to quantify the financial benefit of investing in acacia by farmers in the study area (Nigussie et al. 2020). However, in this study, a farm-level decision model that captures the study area's complex farming system is developed. As discussed in the methodology section, the model allows interactions between sectors - crop production, livestock production, and forestry, a more holistic approach than a financial analysis such as NPV. Besides, the model integrates farmers' objectives of fulfilling their minimum food (protein and energy) and essential non-food consumption while quantifying acacia's economic benefits as part of the optimization problem. Furthermore, smallholders in the study area have a heterogeneous distribution of endowments such as land and labor, as shown in Figure 4.1 and Figure 4.2. Since investment in acacia is a land-based investment, the returns depend on the farmers' endowments, especially farm size. As a result, disentangling the effects of an investment in acacia based on endowments gives a better understanding of the effect under farmers' heterogeneity.

The effect of investment in acacia also depends on shocks and agents' ex-ante planning. The research simulates the effect of investment on acacia on aggregated land-use shares and income for the coming ten years depending on whether agents do ex-ante planning and/or there is a covariate shock in the area. One of the advantages of using agent-based modeling in this study is that it enables us to capture ex-ante risk consideration by agents (Berger and Troost 2014). With their risk expectations, agents operate safely in the model if they adopt precautionary ex-ante planning in their farm operations. Farming in a *safe mode* gives agents the ability to smooth farm operations for any possible occurrence of a future shock in their planning horizon. At its weakest point, operating in safe mode might force agents to opt for decisions leading to lower objective value compared to the situation where they expect the future to have no risks or if they chose to do nothing about it. This forces them to allocate their scarce resources in less favored options. By comparing with the counterfactual scenario where agents are not planning for future shocks', the opportunity cost of ex-ante planning for shocks can be quantified.

The effectiveness of ex-ante planning of agents is tested by introducing shocks in the model's actual simulation years. Pests and crop diseases frequently occur in the study area. According to the 2018 survey, 53% of the sample farmers reported that pests and

crop disease have the most severe consequences to their livelihood than other covariate shocks. Since potatoes and acacia have higher aggregated land-use share in the study area, potato late blight and acacia seedling disease are considered to assess effects on aggregated land-use shares and total discretionary income. Studies show that late blight reduces potato yield by a substantial amount. Hirut et al. (2017) in their study showed that late blight in the study area causes a yield loss of 50.2% on average, ranging from 16% to 88%. Moreover, acacia seedling disease poses a significant threat to acacia decurrens production in the study area. From the interactive model validation with experts, it has been understood that in 2020 acacia seedling disease has been widely witnessed in the area, which forces farmers to plow over the dried seedlings to prepare the land for the next production period.

These facts raise a scientific curiosity to measure the effects of these crop diseases on agents' livelihood and the effectiveness of ex-ante planning thereof. As a result, late blight is introduced as a common potato disease in the study area in the second simulation period (2019). The results are compared with counterfactual scenarios to see the effect on outcome variables. Moreover, acacia decurrens disease is introduced in the second year and compared the results in the same fashion as of late blight. Furthermore, to see the effectiveness of ex-ante planning by agents in the worst cases, potato late blight and acacia disease are introduced in the fourth year - 2021.

Therefore, this simulation experiment's purposes are (first) to examine the effect of investment in acacia on land use shares and income and (second) to see the effect of ex-ante planning in the presence of covariate shocks on land-use share and income in the study area.

Simulation experiment design

To understand the effect of investment in acacia and the role of ex-ante planning on farmers' livelihood in the study area, scenarios are defined based on agents' willingness to plan for shocks on *ex-ante facto* basis, whether an investment in acacia is allowed or not and the occurrence of shock (late blight in the second year, acacia seedling disease in the second year and late blight and acacia seedling disease in the fourth year).

Accordingly, the effect of ex-ante planning for all disease and no-disease scenarios. A total of eight comparisons were done. For no disease scenarios, the results from NPA with NRA were compared. Besides, the results of BPA with BRA were compared and for the other two shocks in a similar fashion. Scenario definition of the effect of ex-ante planning on agents' livelihoods is presented in Table 5.1. land-use in hectares, land-use share and cash income are used as an outcome variable to compare the effect.

Table 5.1: Scenario definitions: Effects of ex-ante planning for shocks and investment on AD.

Crop/tree disease scenarios	<i>Simulation experiment 1: scenario definition</i>		
	Ex-ante planning (P)	No ex-ante planning (R)	Acacia adoption scenarios
Normal year (N)	NPA	NRA	Allow investment in Acacia (A)
Normal year (N)	NPO	NRO	No investment in Acacia (O)
Shock year: second year is late blight year (B)	BPA	BRA	Allow investment in Acacia (A)
Shock year: second year is acacia disease year (S)	SPA	SRA	Allow investment in Acacia (A)
Shock year: fourth year is late blight and acacia disease year (C)	CPA	CRA	Allow investment in Acacia (A)

Outcome variables

The model outcome variables used in this simulation experiment are income and land use. Discretionary income is the working definition of income throughout the thesis. Discretionary income is defined as agent's income after food and essential non-food expenditures are covered. Discretionary income is the appropriate measure for agent's income specially when substantial portion of income goes to food and basic non-food items. The other outcome variable is land-use. Land use shares are used instead of absolute values to capture the difference irrespective of the heterogeneity in farm size. The same outcome variables are also used for the second simulation experiment.

Uncertainty analysis

Some variables and parameters, including yields and prices, used as an input in the model are determined exogenously. Results from simulation experiments, in general, are affected due to uncertainty associated with these exogenous variables and parameters. As a result, uncertainty analysis was carried out using the exogenous variables in the model following the approach by Christian Troost and Berger (2014) to corroborate robustness the simulation experiments' results. The study applied Sobol's quasi-random sequence method to select the samples from the full factorial space Tarantola, Becker, and Zeitz (2012).

Table 5.2: Description of uncertainty variables and model parameters

Variable	<i>Values are in standardized percentage change</i>			
	Description	Distribution of sample	Min. value	Max. value
Potatoes yield	variation factor	Uniform	0.50	1.50
Wheat yield	variation factor	Uniform	0.50	1.50
Barley yield	variation factor	Uniform	0.50	1.50
Teff yield	variation factor	Uniform	0.50	1.50
Acacia charcoal price	variation factor	Uniform	0.50	1.50
Bamboo culm price	variation factor	Uniform	0.50	1.50
Potatoes price	variation factor	Uniform	0.50	1.50
Teff price	variation factor	Uniform	0.50	1.50
Wheat price	variation factor	Uniform	0.50	1.50
Barley price	variation factor	Uniform	0.50	1.50
UREA price	variation factor	Uniform	0.50	1.50
DAP price	variation factor	Uniform	0.50	1.50
Milk yield	variation factor	Uniform	0.50	1.50
Meat yield	variation factor	Uniform	0.50	1.50
Inflation rate	variation factor	Uniform	1.00	1.30
Discount rate	variation factor	Uniform	0.02	0.09

Accordingly, a total of 16 uncertainty variables and parameters were selected that fall under the category of crop and tree product yields, livestock output, output prices, input prices and financial parameters (interest rates, inflation rates and discount rate). Table 5.2 presents description of uncertainty variables and model parameters used in the uncertainty analysis.

Simulations were run for 40 repetitions¹ and all the results on outcome variables for this simulation experiment is summarized for the 72 agents in the model over these sample repetitions. Following the methods used in Figure 5.1 shows the convergence of discretionary income of agents over sample points in the sobol sequence. Annual discretionary income is presented at its mean value, 95th percentile and 5th percentile to show how much it diverges across the sample. The result shows a annual discretionary income converges quickly and have a relative steady state value in repeated samples - which shows the robustness of the results.

¹Selection of number of repetitions is based on the minimum number of sample size required to make statistical inferences afterwards, i.e, $n = 30$

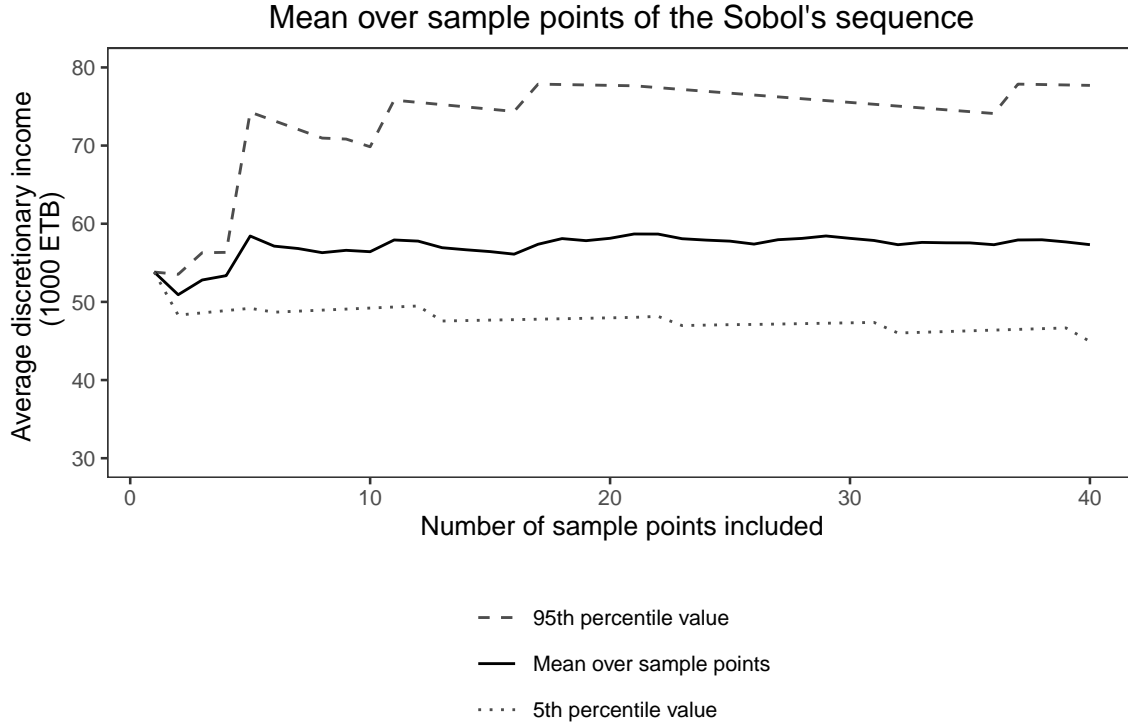


Figure 5.1: Convergence of average annual discretionary income over the Sobol sequence

5.1.1 *Effect of investment in acacia on land-use*

Land use shares² are used instead of actual land-use values to show the effect of investment in acacia on land-use decisions. This helps us to see the effect irrespective of differences in farm size across agents. The results on the effect of farm size on land use shares is shown separately afterwards. Accordingly, Figure 5.2 displays land-use shares of crops and trees grown by agents in the model with and without investment in acacia. Simulations were run for ten years starting from 2018. The values are aggregated over sample repetitions for all agents in each simulation period. In the baseline scenario where there is investment in acacia, acacia has an aggregated land-use share of 41%, followed by potatoes (32.8%), wheat (22.9%) and pasture (8%) in each simulation period on average. On the other hand, in the scenario where there is no investment in acacia, agents opt to produce crops where potatoes (40.4%) and wheat (39%) take the lion's share. Agents also grow pasture (10.9%) and teff (8.9%) in a relatively smaller land share.

²Land-use share is calculated at agent level by dividing total area of a crop or tree by total farm size of the agent in each period

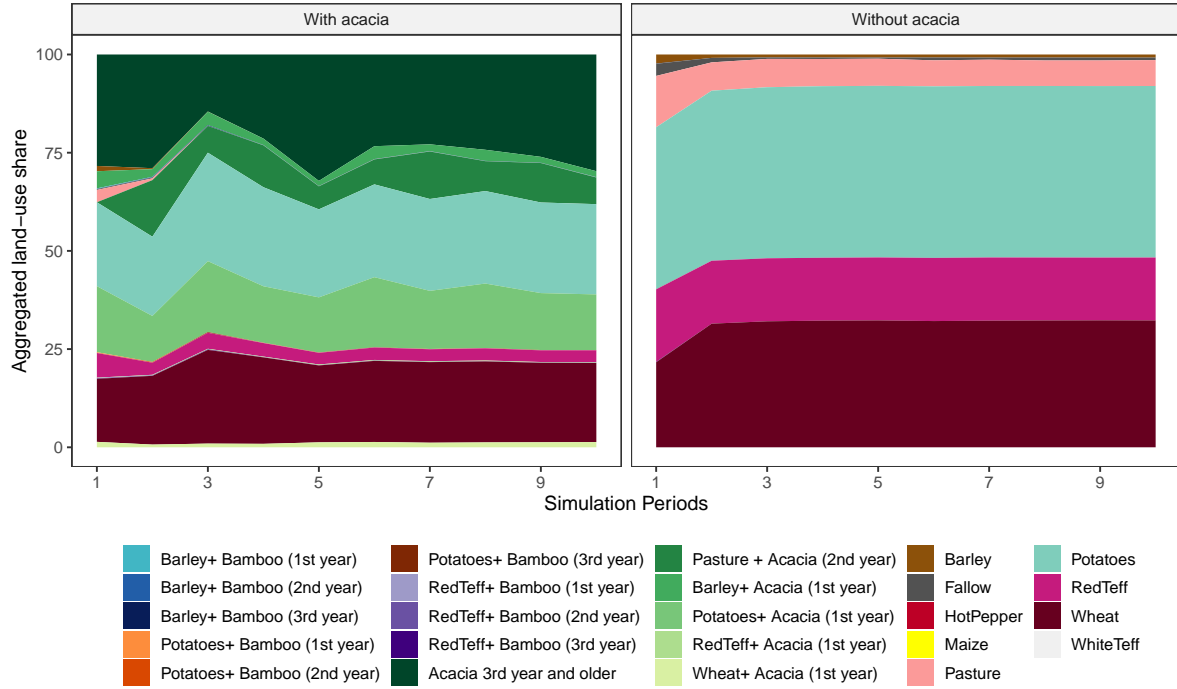


Figure 5.2: Land-use share in the baseline scenario

Land use shares with investment in acacia are subtracted from those without acacia to examine the effects of investment in acacia on land use shares for each agent in each repetition and in each simulation period. The results show that the share of wheat decreases by 16% as acacia takes over 42.5% of the aggregated land-use share on average. Likewise, the percentage of teff, potatoes and pasture reduce by 8.3%, 7.6% and 2.8%, respectively on average. Figure 5.3 shows the difference in aggregated land-use shares attributed to investment in acacia.

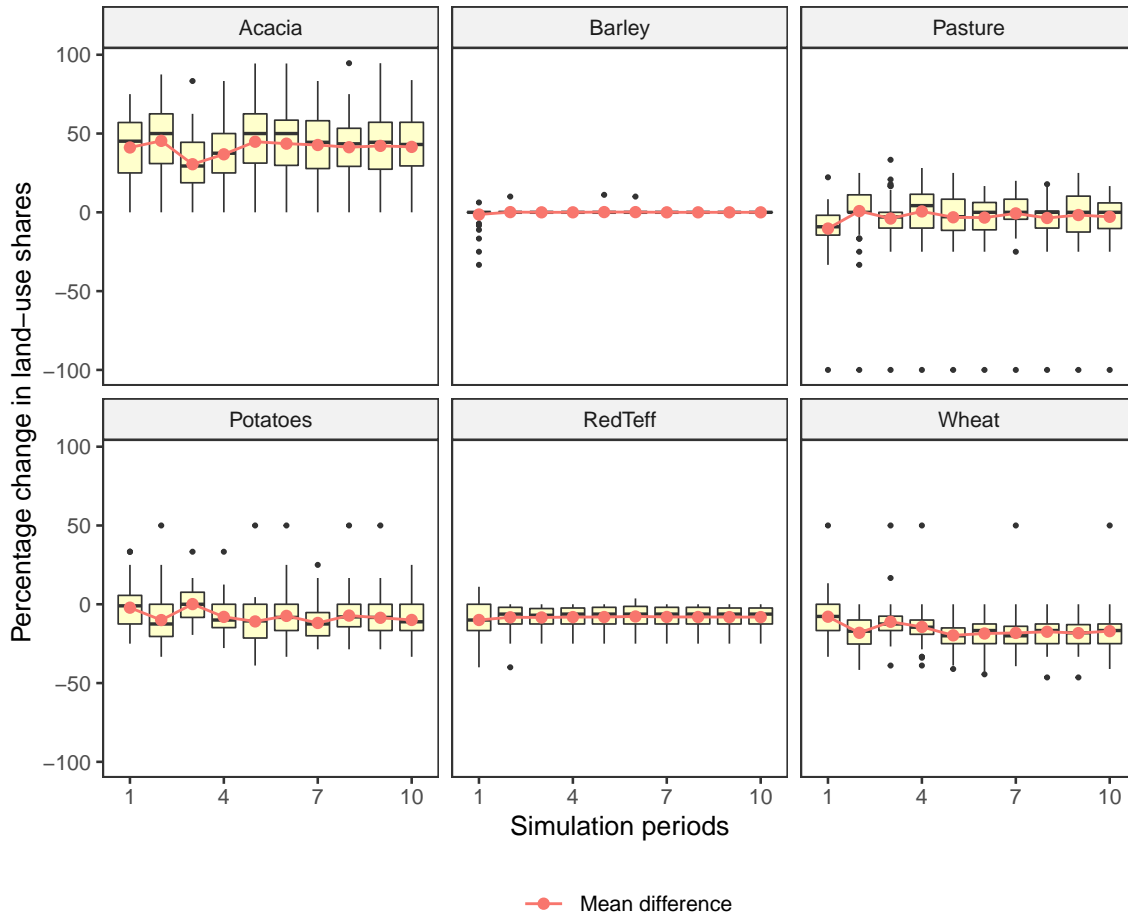


Figure 5.3: Effect of investment in acacia on aggregated land-use

The difference in actual land-use in hectares between the two scenarios is calculated and plotted against farm size to see if there is systematic relationship. With investment in acacia, area covered in acacia and pasture have a positive relationship with farm size whereas potatoes and wheat decrease as farm size increases. The results on acacia is straight forward as there is no investment in acacia in the counterfactual scenario. However, the results on crops show that agents allocate lower and lower land to crops as their farm size increases. Figure 5.4 shows scatter plot of farm size and difference in land use in ha and a fitted line.

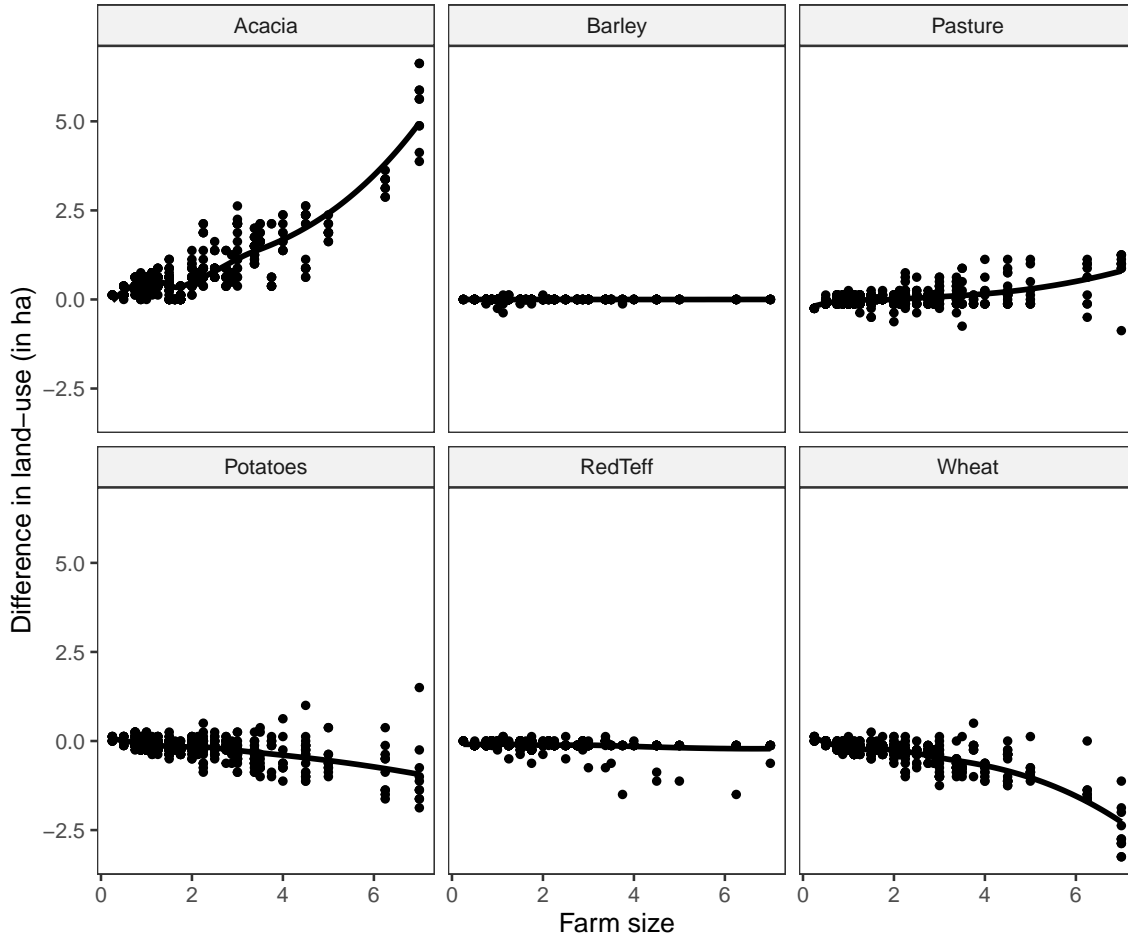


Figure 5.4: Scatter plot of actual land-use difference by farm size

5.1.2 *Effect of investment on discretionary income*

Simulation results show that agents get higher discretionary income with investment in acacia on average. The average annual discretionary income of agents in the baseline is 58,738 ETB, whereas the average per capita discretionary income is 11,631 ETB per year. Figure 5.5 shows distribution of total and per capita annual discretionary income of agents for 10 simulation periods. Agents get 7.8% higher annual discretionary income with investment in acacia. The increment is a bit higher at the per capita level (8.1%). Figure 5.6 and Figure 5.7 show average annual discretionary income and average annual per capita discretionary income respectively both with and without investment in acacia. Both figures depict that discretionary income with acacia is oscillatory across simulation periods while it is smooth without acacia. This is due to the cycles of acacia and the fact that it is harvested every four years from planting. The figure also shows higher discretionary income in the third simulation period. This is attributed to the initial standing trees agents had at the beginning of the planning period, most of which is harvested at the end of the second simulation period.

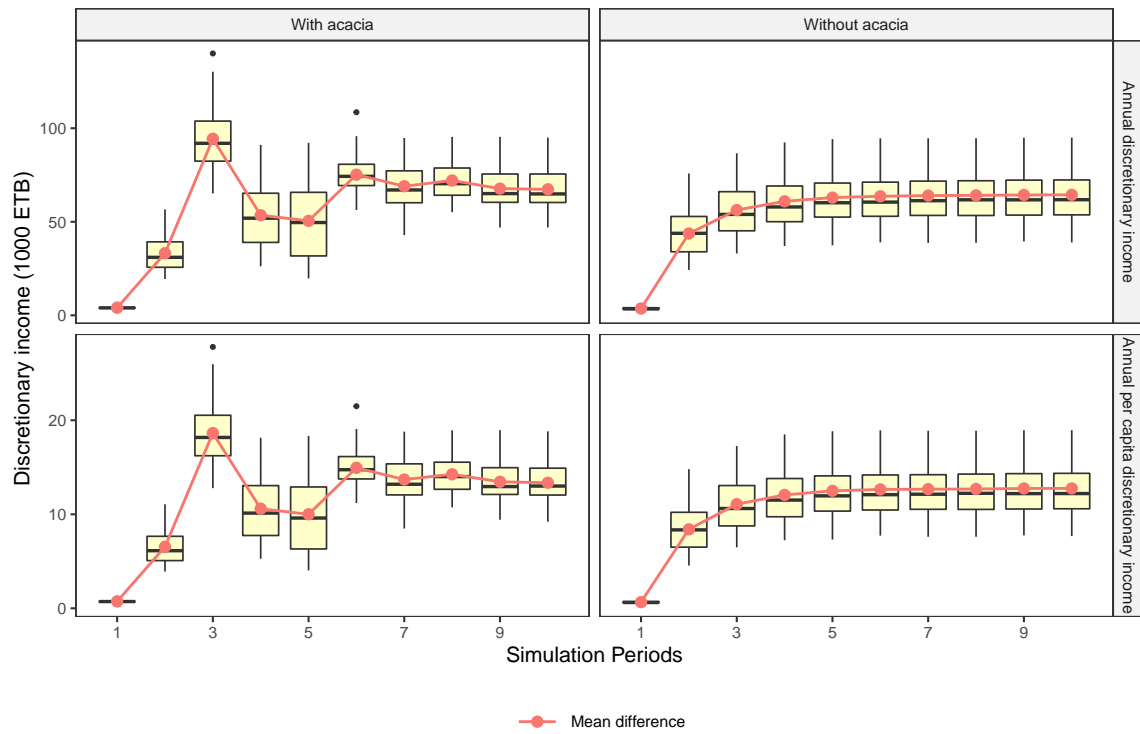


Figure 5.5: Average annual discretionary income

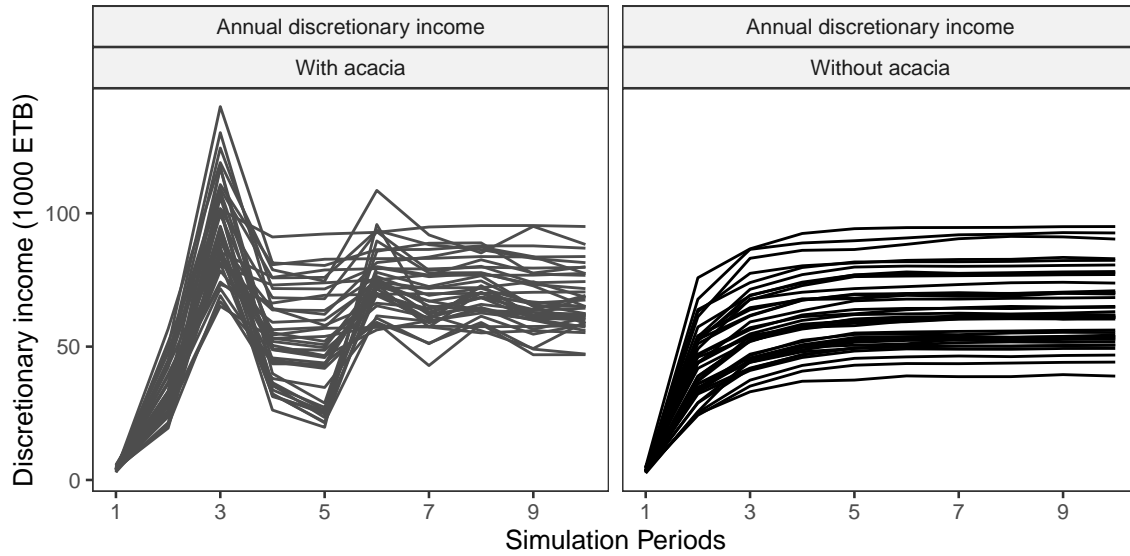


Figure 5.6: Average annual discretionary income

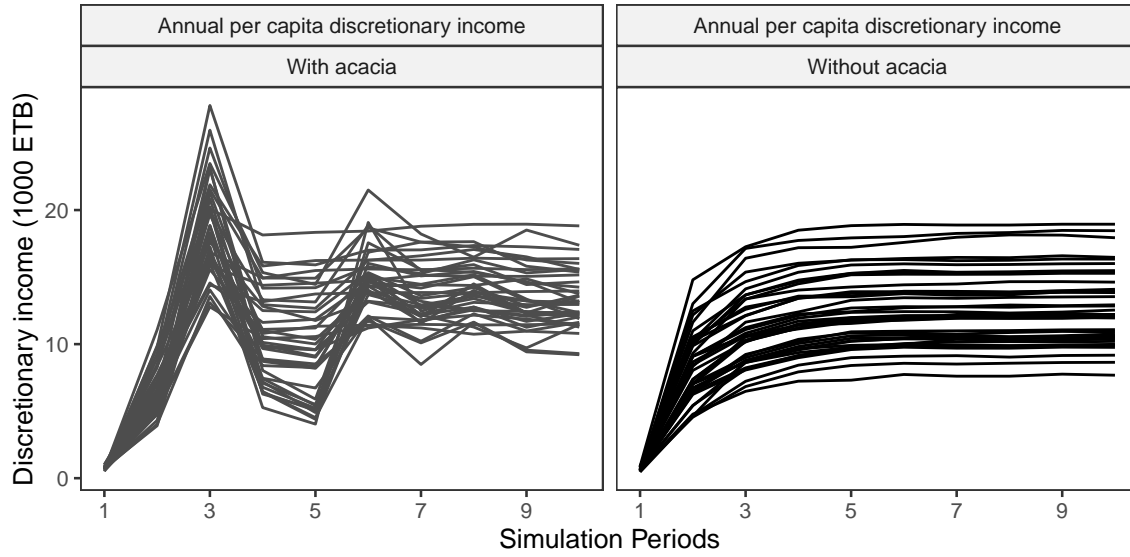


Figure 5.7: Average annual per capita discretionary income

Simulation result also shows that agents fulfill their minimum non-food expenditure better with acacia than without acacia. In both scenarios, the average non-food expenditure deficit is close to zero except for few agents in the first few simulation periods who could not get enough inputs such as labor to produce to their total capacity. However, the rest of the agents were able to fulfill their minimum cash requirements for their essential non-food expenditure in all simulation periods. Figure 5.8 shows the average annual non-food expenditure deficit. The figure shows non-food expenditure deficit disappears quickly over the simulation periods if agents are investing in acacia.

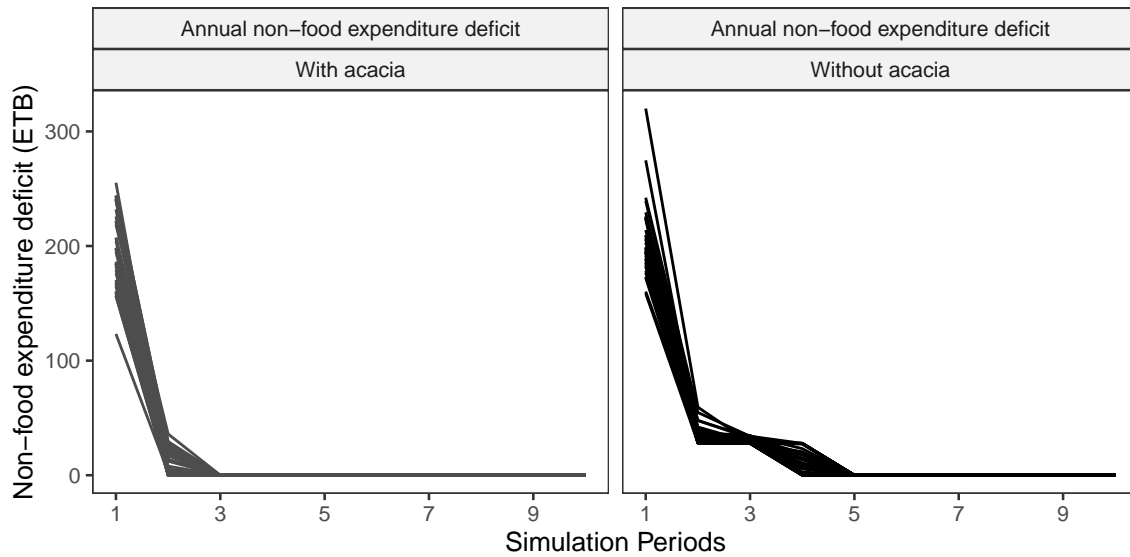


Figure 5.8: Average annual non-food expenditure deficit

The average annual non-food expenditure deficit is plotted in Figure 5.9 against farm

size and a fitted value to understand if there is a systematic relationship between agents' non-food expenditure deficit and their farm size. The result shows agents who have smaller farm sizes are the ones with the deficit, which is plausible. The result is consistent both with and without investment in acacia.

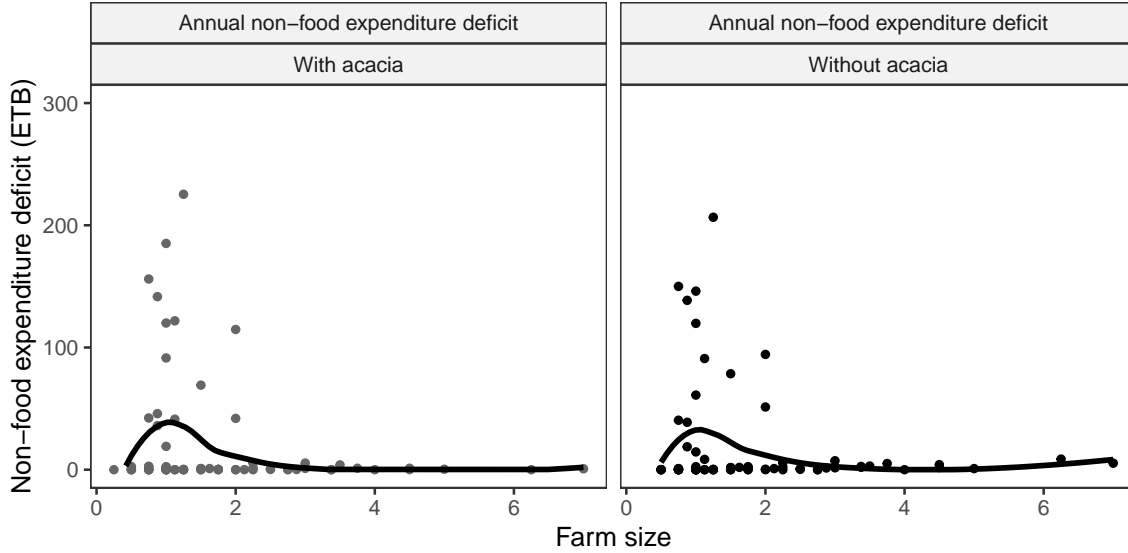


Figure 5.9: Average annual non-food expenditure deficit by farm size

5.1.3 *Effect of shocks on land-use*

Figure 5.10 shows aggregated land-use shares of agents for all shock and non-shock scenarios with and without ex-ante planning. Acacia decurrens, potatoes and wheat have high aggregated land-use shares throughout the scenarios. As shown before the baseline scenario where there is no shock, acacia has an aggregated land-use share of 41%, followed by potatoes (32.8%) and wheat (22.9%) on average. Similar patterns are observed in the late blight scenario with ex-ante planning for shocks. The aggregated land-use share of acacia is reduced to 38.7% in the acacia seedling disease scenario, whereas shares of potatoes and wheat increase to 34.8% and 24.2% on average, respectively. In the worst-case scenario where agents face both late blight for potatoes and acacia seedling disease land use share of acacia has 39.8% land use share on average followed by potatoes (34.4%), wheat (23.6%) and pasture(7.5%) respectively.

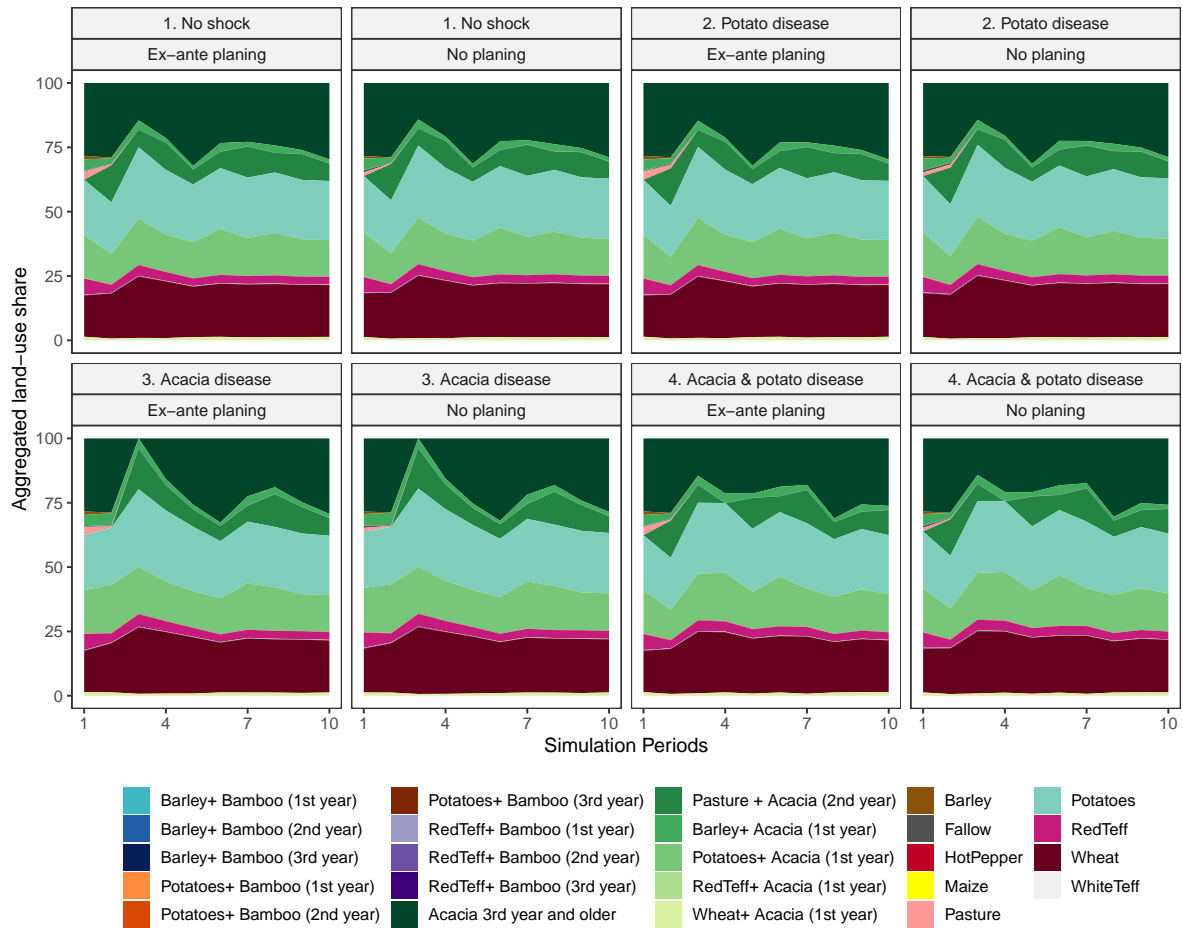


Figure 5.10: Land-use share in shock and no shock scenarios

The percentage change in aggregated land-use share of trees and crops of the ex-ante planning scenarios with no-ex-ante planning scenarios is compared to see the effect of ex-ante planning. The comparison is done for all shock and no-shock scenarios and the results are shown in Figure 5.11 to Figure 5.14.

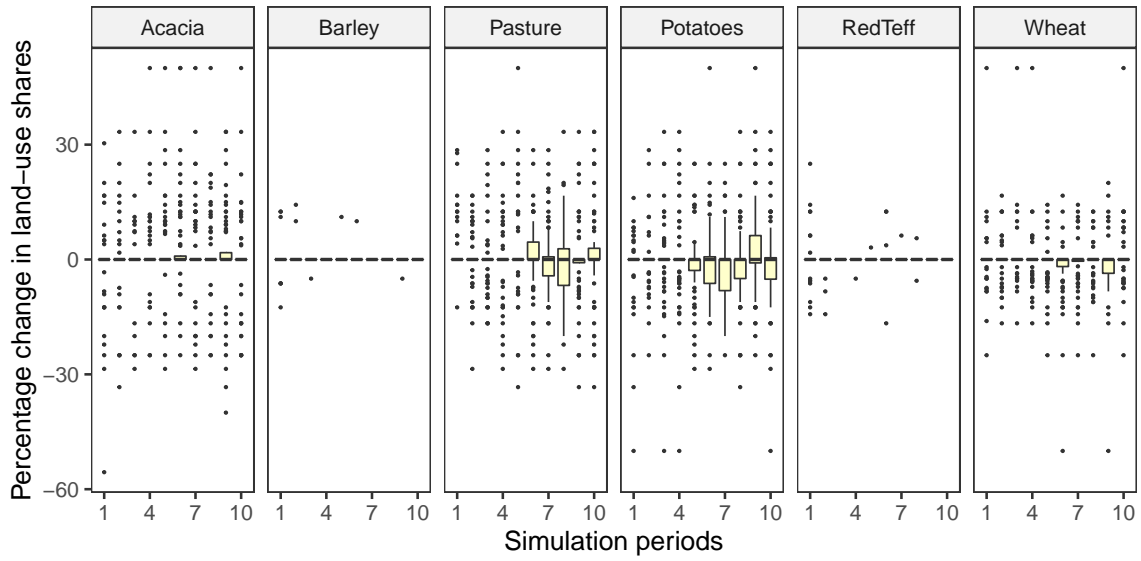


Figure 5.11: No shocks

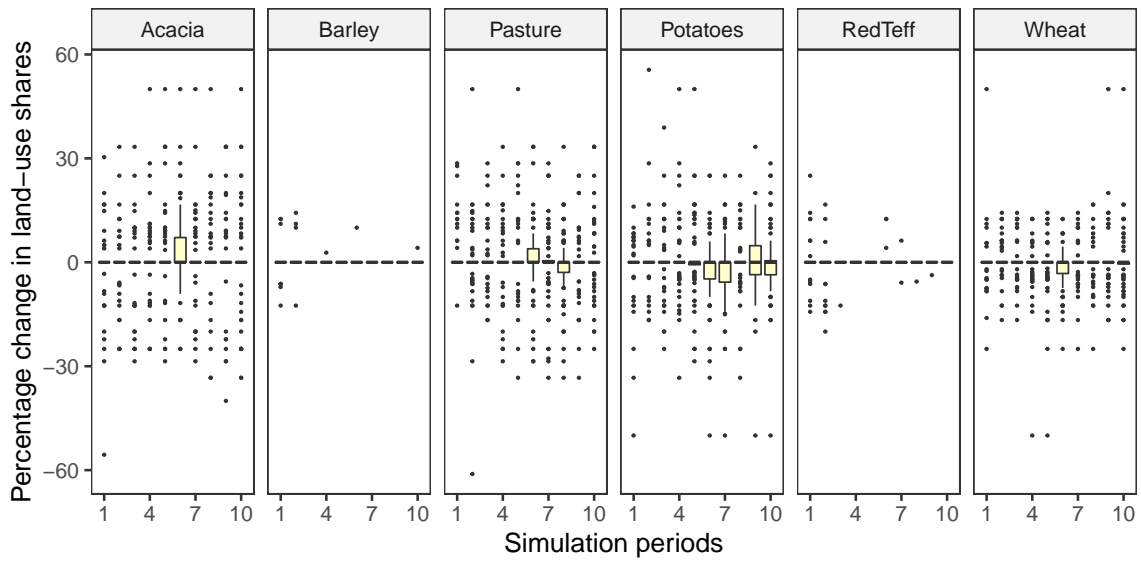


Figure 5.12: Potatoe late blight

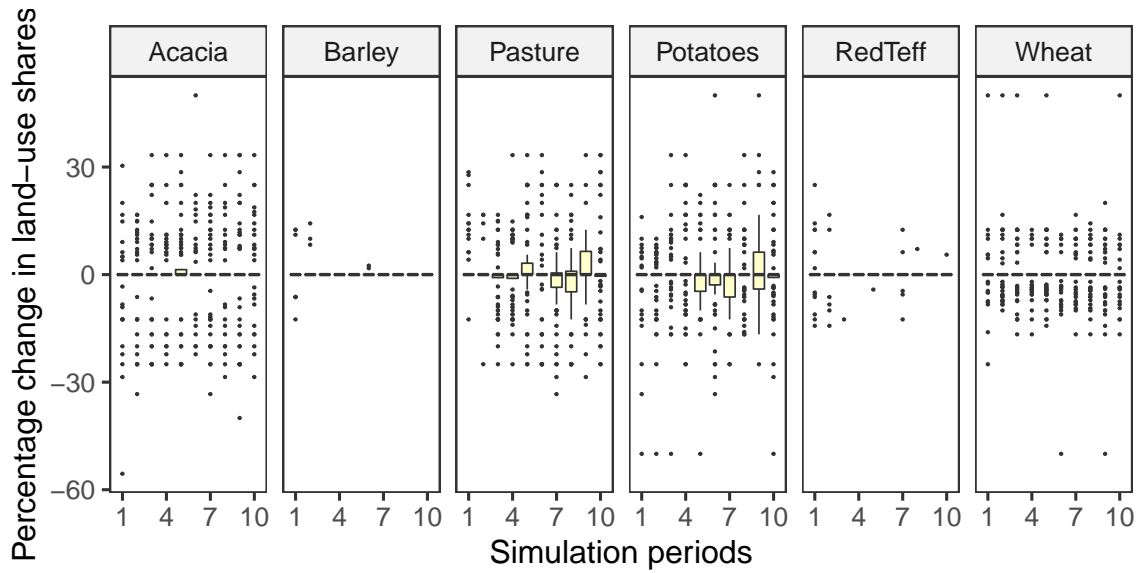


Figure 5.13: Acacia seedling disease

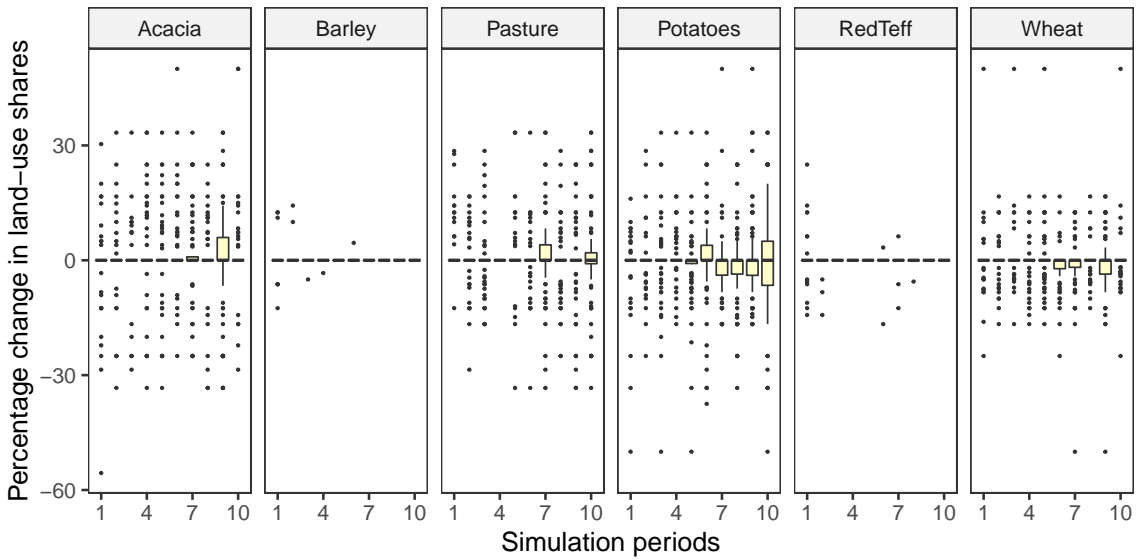


Figure 5.14: Potatoes late blight and acacia seedling disease

Figures show that the magnitude of the ex-ante planning effect on aggregated land-use is small. It is perhaps related to the limited number of cropping options and technologies available for agents. Or, it is related to the fact that agents are resource constrained which hinders them to focus on few cropping options. Acacia land-use share increases by 1% to 2% on average if agents have ex-ante plans for future shocks. Potatoes land share decreases by 1% to 1.5% on average except during late blight, where there is no ex-ante planning effect. Likewise, wheat land-use share decreases from 0.5% to 1% on average throughout shocks. Though the magnitude of the ex-ante planning effect on land-use shares is small, the direction of the effect tells agents' preferences in choosing

adaptation measures to deal with shocks. The trade-off between trees and crops by agents show that they prefer to plant trees than crops as part of their ex-ante plan for shocks.

5.1.4 *Effect of shocks on discretionary income*

Figure 5.15 and Figure 5.16 show average annual discretionary income and average per capita discretionary income of agents in all scenarios. On average, the yearly discretionary income ranges from a minimum of 56.5 thousand ETB in potato disease scenario to maximum 59 thousand ETB in scenario without shocks. If we look closely at the simulation periods where the shocks occur, we observe the difference in average annual discretionary income attributed to shocks. Figure 5.17 and Figure 5.18 show the effects of shocks on per capita discretionary income with and without ex-ante planning.

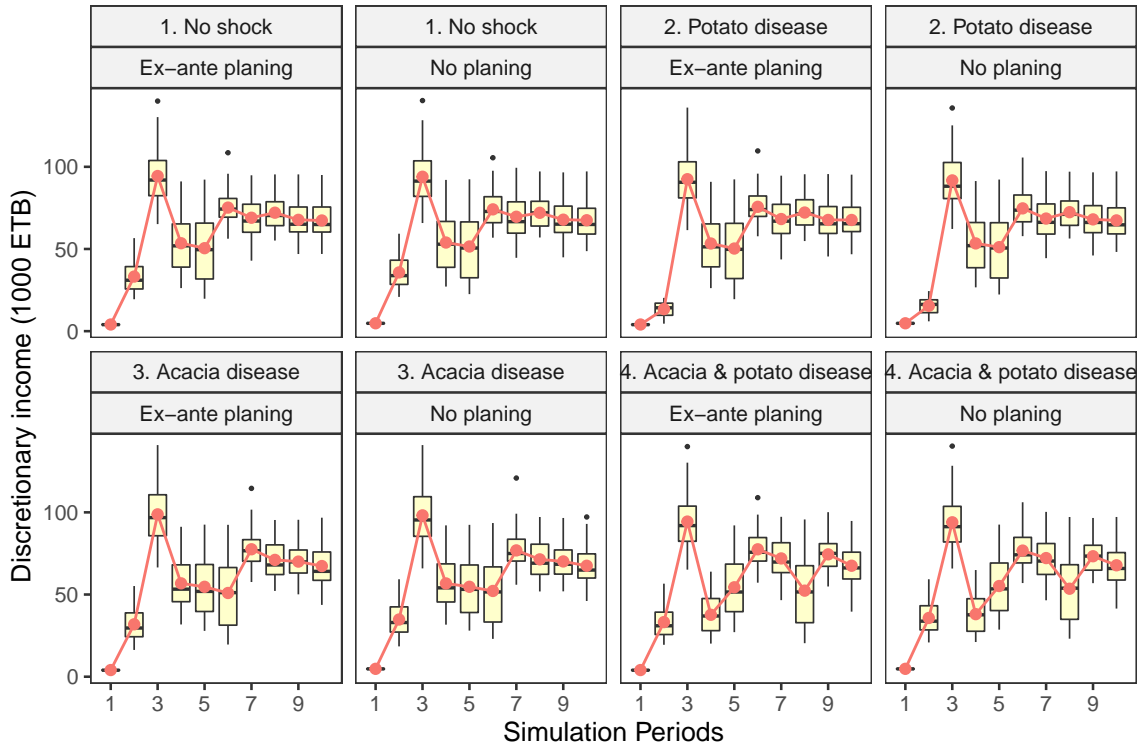


Figure 5.15: Average annual discretionary income

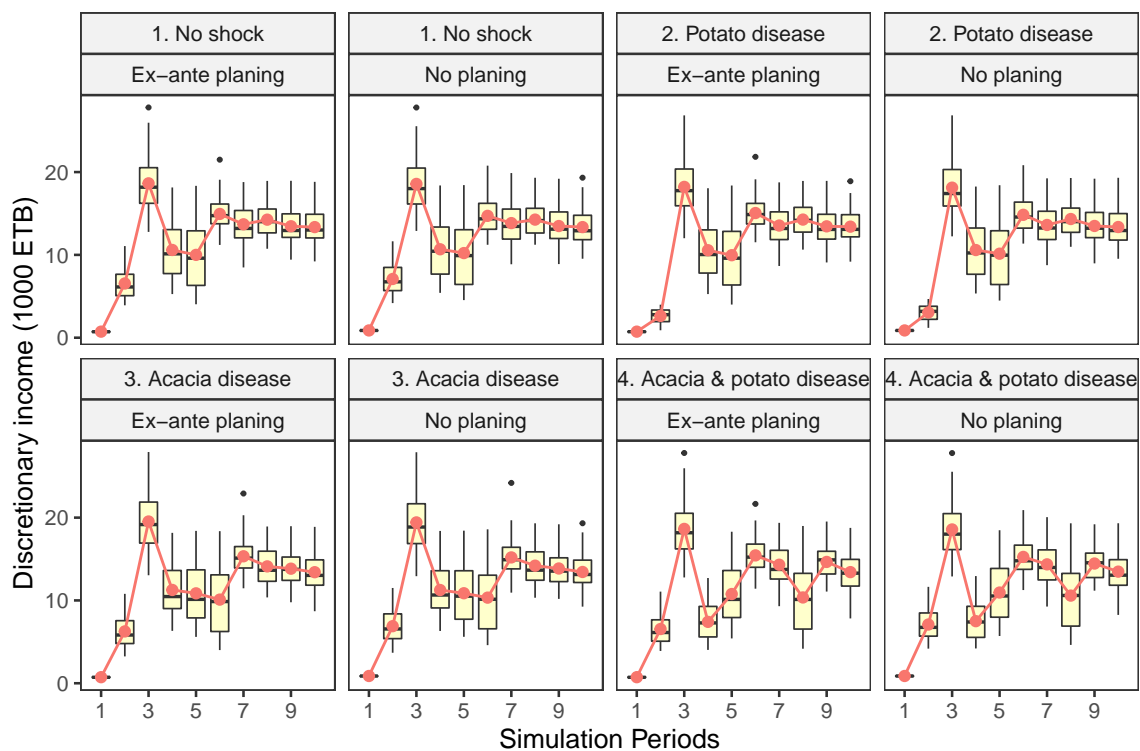


Figure 5.16: Average annual discretionary income

The effect of shocks on annual per capita discretionary income when agents' are planning for future shocks is presented in Figure 5.17. In 2019, potato late blight reduced agents' annual discretionary income by 58.7% compared to the baseline - reducing the average per capita discretionary income to 2.7 thousand ETB in the same period. In addition, occurrence of acacia seedling disease in the fourth period only reduces average per capita discretionary income by 2.7%. As the yield from investment in acacia is realized after the fourth year from the shock year, except for the loss in input costs for acacia in the first year, a direct effect on per capita discretionary income is expected in the coming simulation periods than the shock year. In connection with this, the average discretionary income decreases by 31% after four years in 2023 - which is highly likely associated to the acacia shock in fourth period. Furthermore, in the fourth year (2021), when potato late blight and acacia seedling disease coincide, annual per capita discretionary income decreases by 27% in the shock year compared to the baseline scenario. And, an additional overdue decrease of another 27% in 2025 because of late effects of acacia seedling disease. Similar values have been obtained from the scenarios without ex-ante planning.

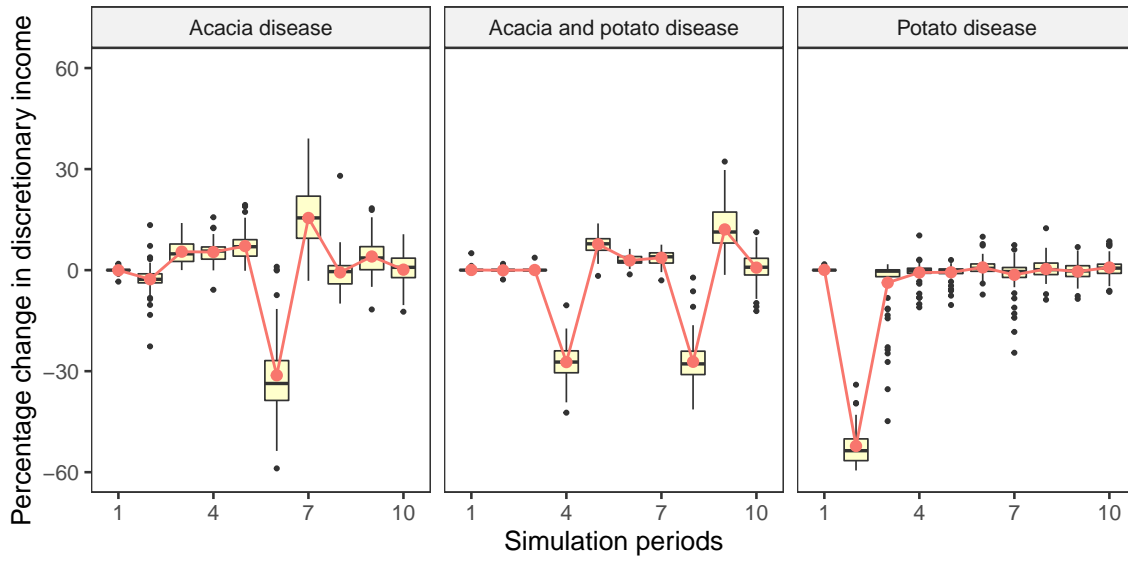


Figure 5.17: Effects of shocks on discretionary income - With Ex-ante planing

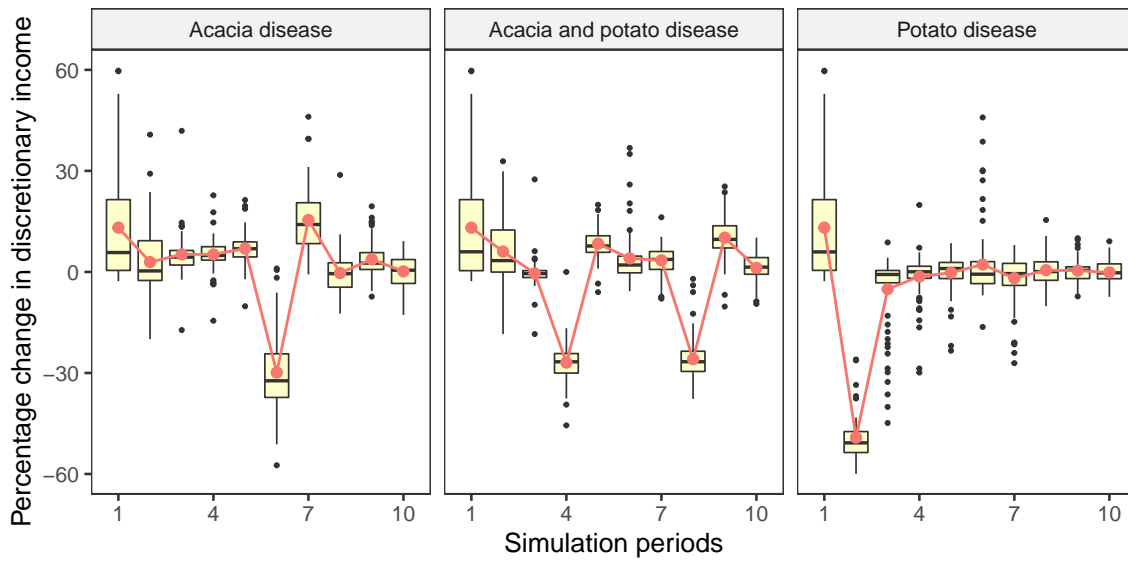


Figure 5.18: Effects of shocks on discretionary income - Without Ex-ante planning

The percapita non-food expenditure deficit is zero for most of the agents, if not a very low amount. Agents who have deficit are the ones who have lower initial endowments. Agents reserve 453 ETB per capita on average in scenarios where there is ex-ante planning.

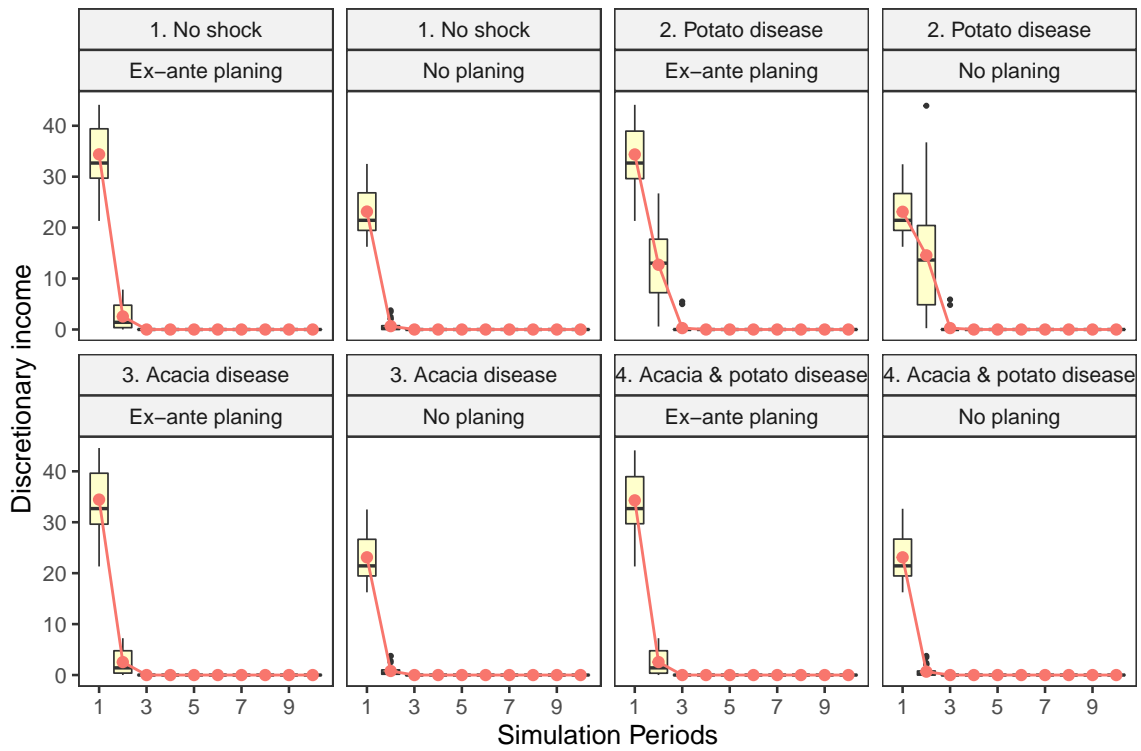


Figure 5.19: Annual percapita non-food expenditure deficit

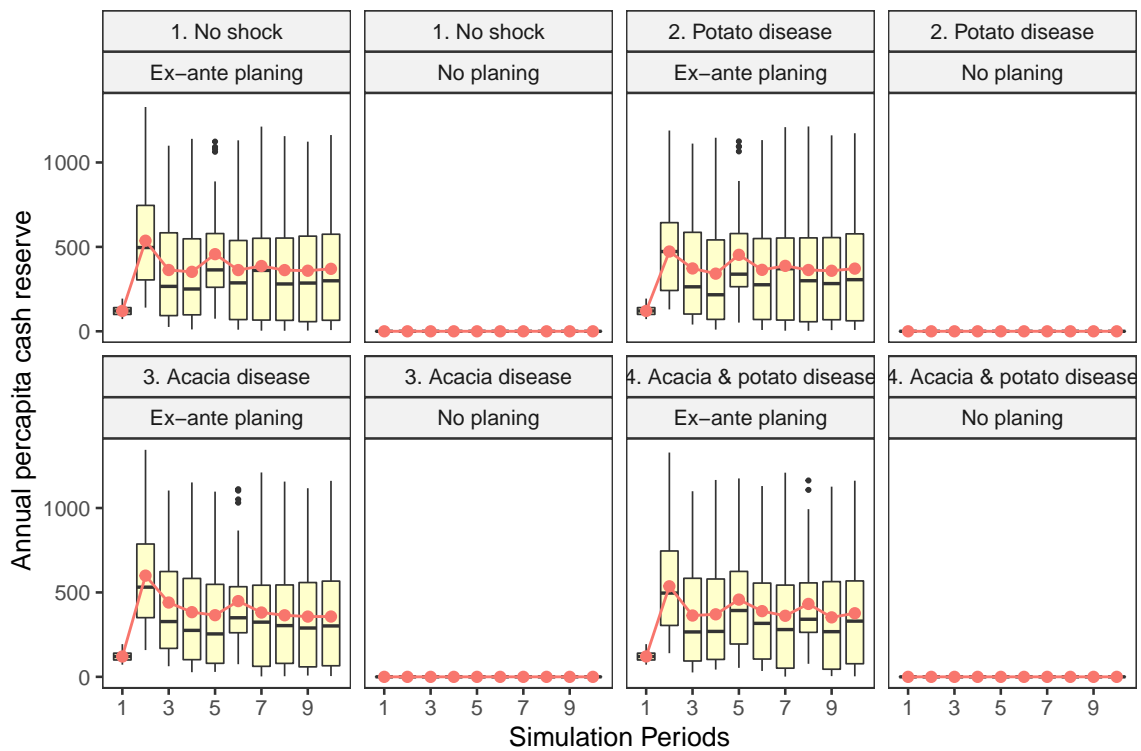


Figure 5.20: Annual per capita cash reserve

5.2 Sustainability of acacia: how responsive are agents to long-run expected price shocks?

Rationale

The second simulation experiment aims at examining the effect of long-run expected price changes mainly on land-use decisions of agents in the model. The purpose of this simulation experiment is to see if there is a deviance from croplands to woodlots and vice versa based on long-run changes in expected prices. The motive comes from the developments related to the expansion of acacia decurrens in the area. Attracted by economic and ecological factors, farmers in the study area have been converting their cropland into acacia woodlots for more than a decade now (Berihun et al. 2019 ; Nigussie et al. 2017). This opportunity has improved the livelihoods of farmers significantly (Nigussie et al. 2020) which is in line with the results obtained in the first simulation experiment. Recently, however, the acacia production in the area has faced a double threat. The first threat is the reduction of farm gate charcoal prices attributed to charcoal mass-production coupled with high transaction cost from the farm to the market and increased involvement of mediators in the supply chain with high price making power. These concerns has been raised both by farmers in FGDs in 2018 and also in the interactive model validation by experts. The second threat is acacia seedling disease. According to experts, in 2020, farmers reported a widespread acacia seedling disease, which forces them to plow over dried seedlings for the next production season.

Parallely, the soil fertility has been improving because of multiple cycles of acacia woodlots planted in the area. Eventually, this has reduced the acidity of the soil and increased crop productivity (Dubiez et al. 2019). Moreover, as part of the country's whole macroeconomic developments, prices of crops have been growing by over 20% annually on average for the last years (CSA 2021). These complementary developments raised a scientific curiosity on how agents' decisions would change in the future. As a result, scenarios with different sets of long-run expected price variability for crops and tree products in the future were established to see the effect.

Simulation experiment design

Scenarios are defined as combinations of a percentage point changes of expected prices of tree products and crops. Acacia charcoal and bamboo culm prices are used to capture long-run price changes in main tree products. Whereas the prices of main crops in the area - potatoes, teff and wheat - are used to change the growth in cereals' prices in the area. The percentage changes in prices were set to a substantial amount (50%) to capture long-run price changes. A 50% increase or decrease in the price of a given product could happen at a particular year but could not be the case all the time. But this can be considered valid in repeated samples in the future. So, the notion of higher price change represents a substantial change in the future prices in the planning horizon.

In the baseline scenario, everything remains unchanged. To see the effect of price changes in tree products on land-use, the baseline scenarios is compared with 50%

Table 5.3: Effects of long-run price changes on agent's decisions

Scenario description	<i>Simulation experiment 2: scenario definition</i>				
	<i>Percentage point change in expected prices of:</i>				
	Acacia	Bamboo	Potatoes	Wheat	Teff
Base line	0	0	0	0	0
Decrease in expected price of charcoal	-50	0	0	0	0
Decrease in expected price of acacia charcoal and bamboo culm	-50	-50	0	0	0
Increase in the expected price of crops	0	0	50	50	50
Decrease in expected price of acacia charcoal and bamboo culm and increase in the expected price of crops	-50	-50	50	50	50

decrease in the price of bamboo culm and 50% decrease in acacia charcoal price. Next, the effect of a simultaneous reduction of tree products' prices by 50% is shown by comparing with the baseline scenario followed by a simultaneous increase in cereals' prices by 50%. Finally, the effect of a concurrent rise in cereal prices and a decrease in tree products' prices by 50% is shown by comparing it with the baseline.

5.2.1 *Effect of long-run price variability on aggregated land-use shares*

Figure 5.21 shows aggregated land-use shares of agents in the model for the baseline and all price scenarios. Relatively different aggregated land-use shares of crops and trees under future price variability compared to the baseline are observed. To understand the effect of price variability, the percentage change of aggregated land-use share of each price scenario from the baseline is presented - growth from the baseline. A closer look at agents' decisions to see how they switch between crops or between crops and trees is shown in the subsequent figures.

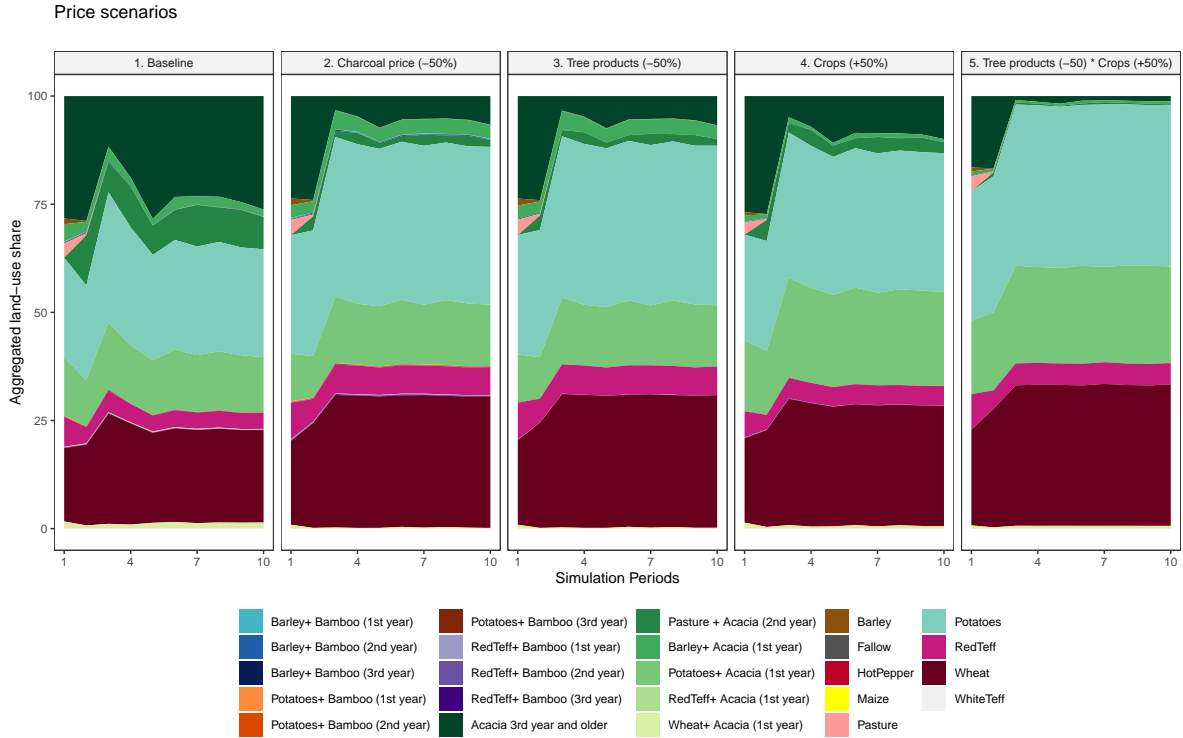


Figure 5.21: Aggregated land-use shares under long-run price variability

First, acacia charcoal price was decreases by 50%, keeping other parameters constant at the baseline value. Figure 5.22 shows the difference in aggregated land-use share of each crop. Agents are highly responsive to the decrease in the price of charcoal by 50%. As a result, land-use share of acacia decreases by 26.5% on average. Whereas the aggregated land-use share of potatoes and wheat increases by 13.5% and 14.3%, respectively. The aggregated land-use shares of bamboo, teff and barley is still meager in this scenario and there is no change from the baseline. With the 50% decrease in expected charcoal price, agents would shift their acacia woodlots into croplands dominated by potatoes and wheat. Figure 5.23 shows the substitution of land-use from trees to crops.

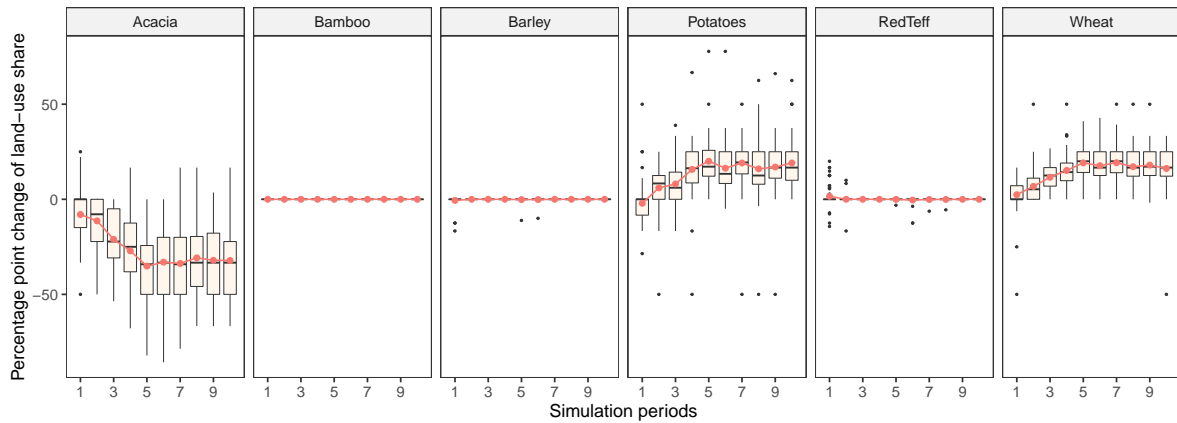


Figure 5.22: Effect of 50 percent decrease in charcoal price on land-use shares of trees and crops

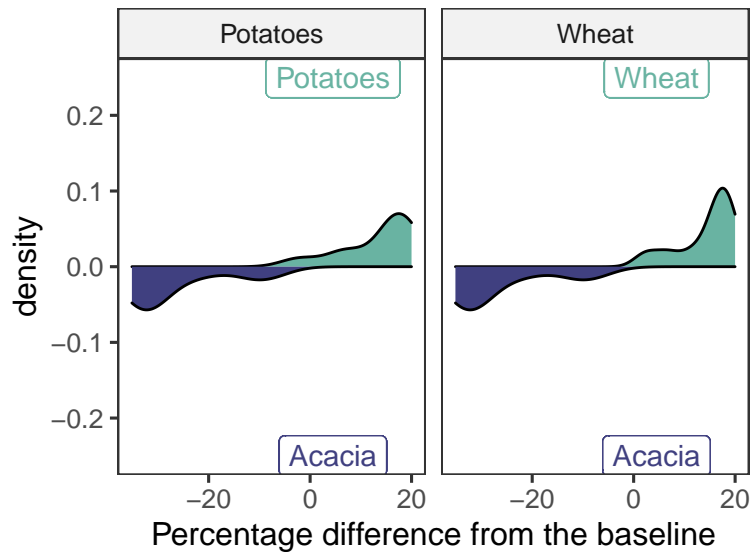


Figure 5.23: Substitution of land-use from woodlots to croplands

Second, the expected prices of tree products' were decreased (acacia charcoal and bamboo culms) by 50% simultaneously to see the effect on aggregated land-use shares in the future. The combined effect of price decrease in bamboo and acacia has a similar effect as the 50% increase in charcoal prices alone. Aggregated land-use share of acacia decreases by 26.6% whereas potatoes and wheat share increases by 13.4% and 14.3% respectively. Provided that farmers can grow bamboo only in the farmstead, it is plausible to see if there is no significant change in aggregated land-use share irrespective of the price stimulus from bamboo. Results on these experiments are shown in Figure 5.24.

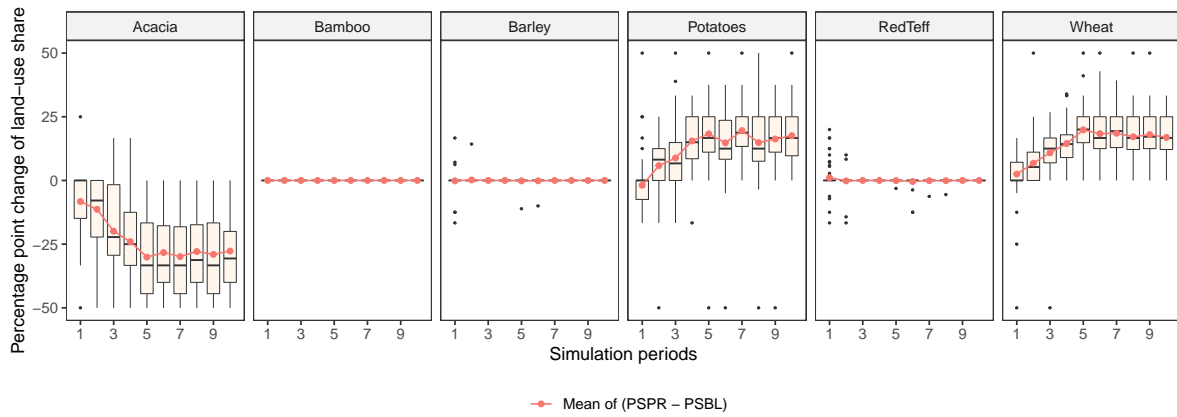


Figure 5.24: Effect of 50 percent decrease in charcoal price and bamboo culm on land-use shares of trees and crops

Third, all expected prices of crops were increased by 50%, keeping other parameters at the baseline value. Agents shift from forestry dominated to crop-dominated production system as a result - similar to the results obtained in the 50% decrease in charcoal's expected price. Figure 5.25 shows the results on aggregated land-use shares. Accordingly, the aggregated land-use share of acacia decreases by 23%, whereas it increases by 8.5% and 12.4% for potatoes and wheat, respectively. Finally, the expected price of crops was increased by 50% and decreased the expected price of tree products by 50% to see the agents' land-use decisions. The results are shown in Figure 5.26. The aggregated land-use of acacia decreases by 28.3%, while that of potatoes and wheat increased by 14.5% and 15%, respectively.

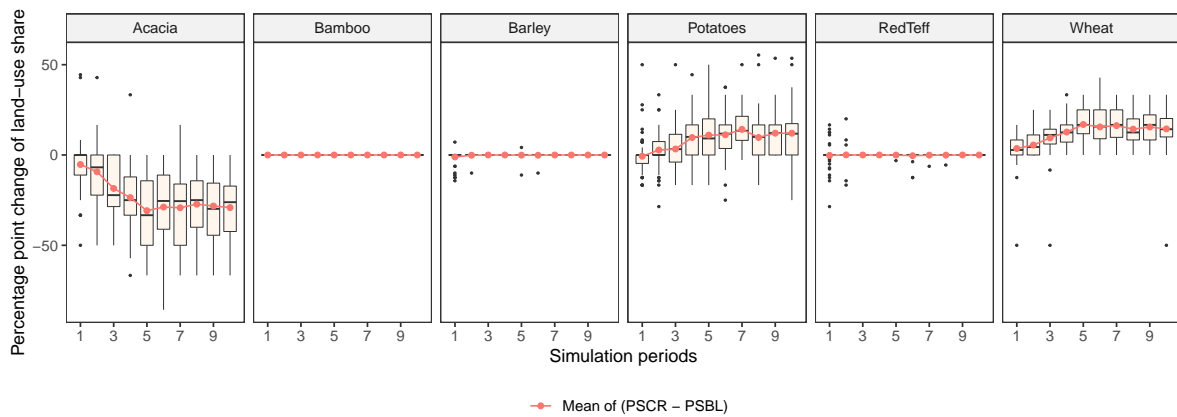


Figure 5.25: Effect of 50 percent increase in crop prices on land-use shares of trees and crops

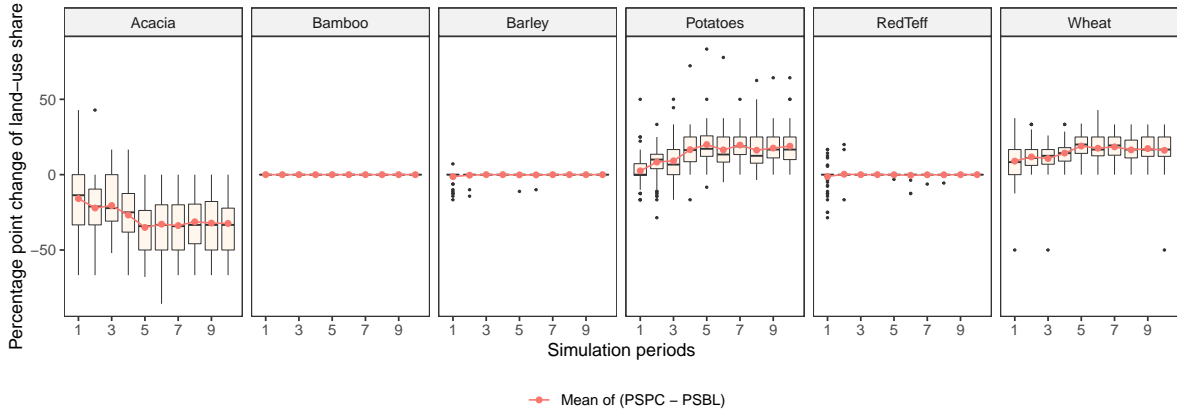


Figure 5.26: Effect of 50 percent decrease in prices of tree products and 50 percent increase in crop prices on land-use shares of trees and crops

5.2.2 *Effects of long-run price variability on discretionary income*

Figure 5.27 and Figure 5.28 show average annual discretionary income and average per capita discretionary income of agents in all scenarios respectively. On average, the yearly discretionary income ranges from a minimum of 42.7 thousand ETB in 50% decrease in the price of charcoal to maximum 58 thousand ETB in 50% increase in the price of crops. The average annual discretionary income of agents in the baseline scenario is 52.2 thousand ETB. Attributed to cost related to acacia investment, the average discretionary income in the first couple of simulation years is lower. Once agents start to harvest acacia, they start getting relatively smoother discretionary income for the subsequent years, which is the same for all price scenarios. Figure 5.27 shows the distribution of annual discretionary income. Since an increase in bamboo's expected price has no effect, it has an almost equal amount of discretionary income as the baseline. Previous results show that these scenarios are acacia dominated scenarios. The oscillations in discretionary income in the two scenarios are related to acacia harvest cycles. In the rest of the scenarios, agents resort to annual crops than trees and have smoother discretionary income throughout the simulation periods.

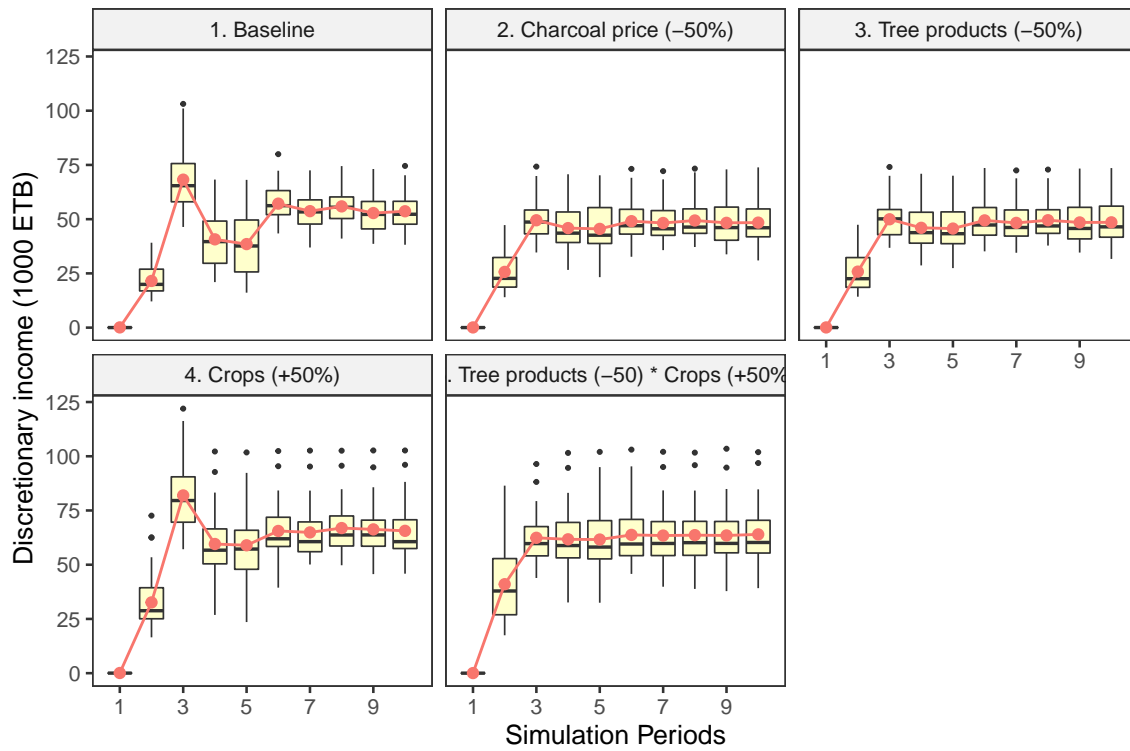


Figure 5.27: Average annual discretionary income

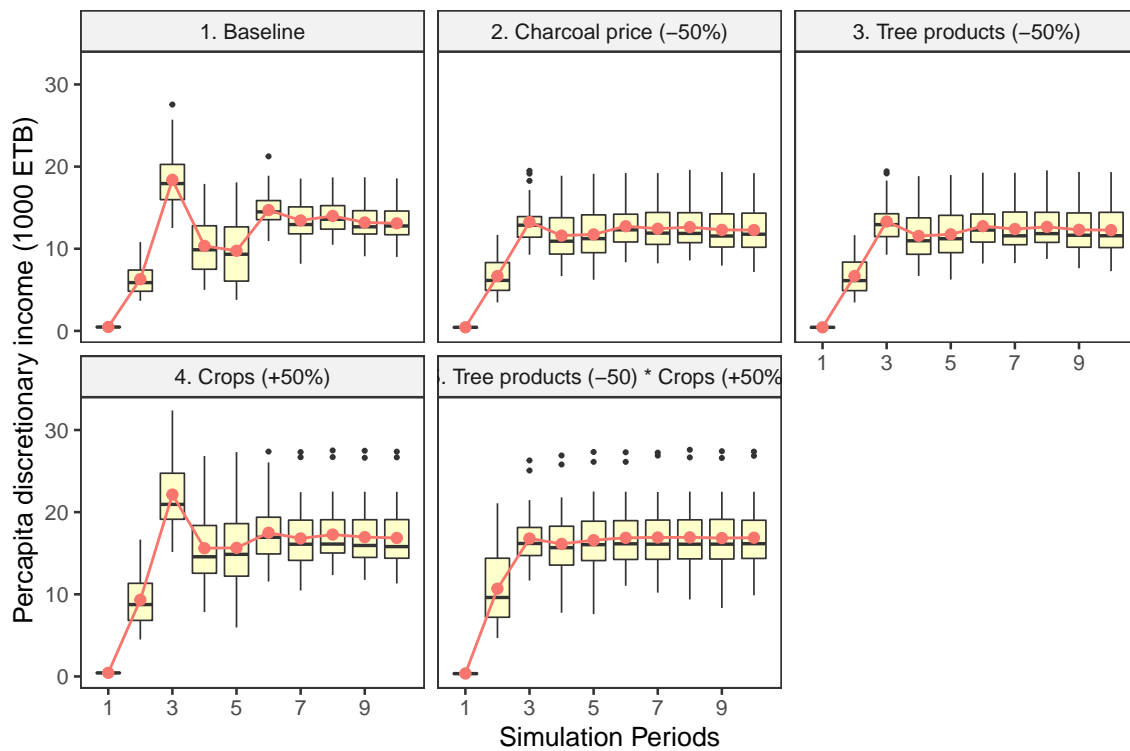


Figure 5.28: Average annual percapita discretionary income

The income effect of changes in expected price is higher for crops than tree products. Figure 5.29 shows that agents earn around 15 thousand ETB more because of a 50% increase in the expected price of crops than a 50% decrease in expected charcoal prices. In other words, agents prefer an increase in the expected crop prices than decrease in charcoal prices to convert their woodlots to croplands. The effect of price shocks on annual per capita discretionary income is presented in Figure 5.29. A 50% decrease in the expected price of charcoal and 50% decrease in the prices of charcoal and bamboo culm simultaneously reduces agents' annual per capita discretionary income by a little bit more than 1% on average per period. On the contrary, both a 50% increase in the expected price of crops all together and a 50% increase in the price of crops and a 50% decrease in the price of tree products occurred at the same period brings agents 27% more income per period.

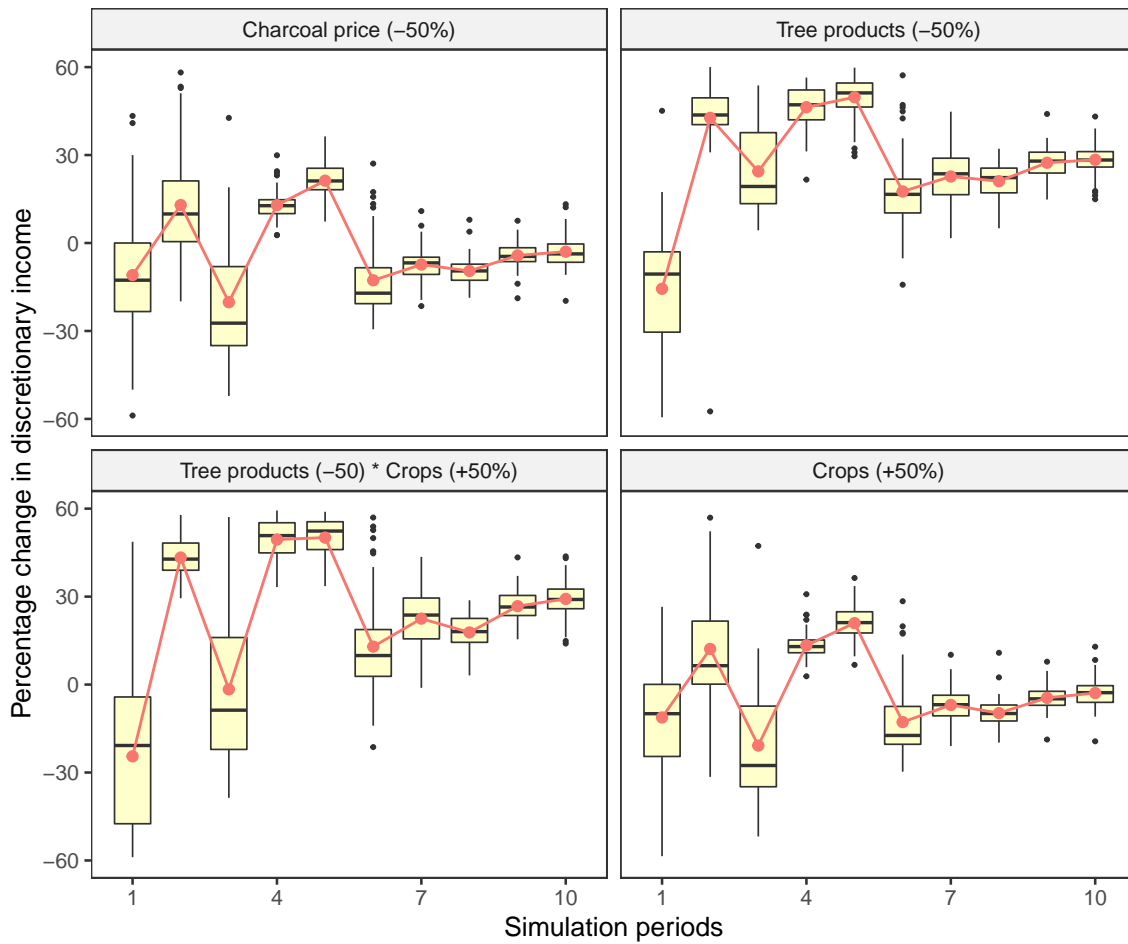


Figure 5.29: Effects of price shocks on discretionary income

Lastly, one of the objectives of the model is to fulfill minimum essential non-food consumption expenditure by agents. The per capita non-food expenditure deficit by agents is calculated using the minimum requirement. The result shows that the average per capita non-food expenditure deficit among agents is almost zero. There are only few

agents who were not able to fulfill their cash consumption. And, this only happens in the first simulation period. The main reasons for the cash deficit for the agents is attributed to low initial endowments such as cash and labor. Furthermore, agents reserve more cash for shocks in the price scenarios than the baseline scenario on average. Agents reserve higher amount of money (2,068 ETB) in the worst case scenario and relatively lower value in the baseline scenario.

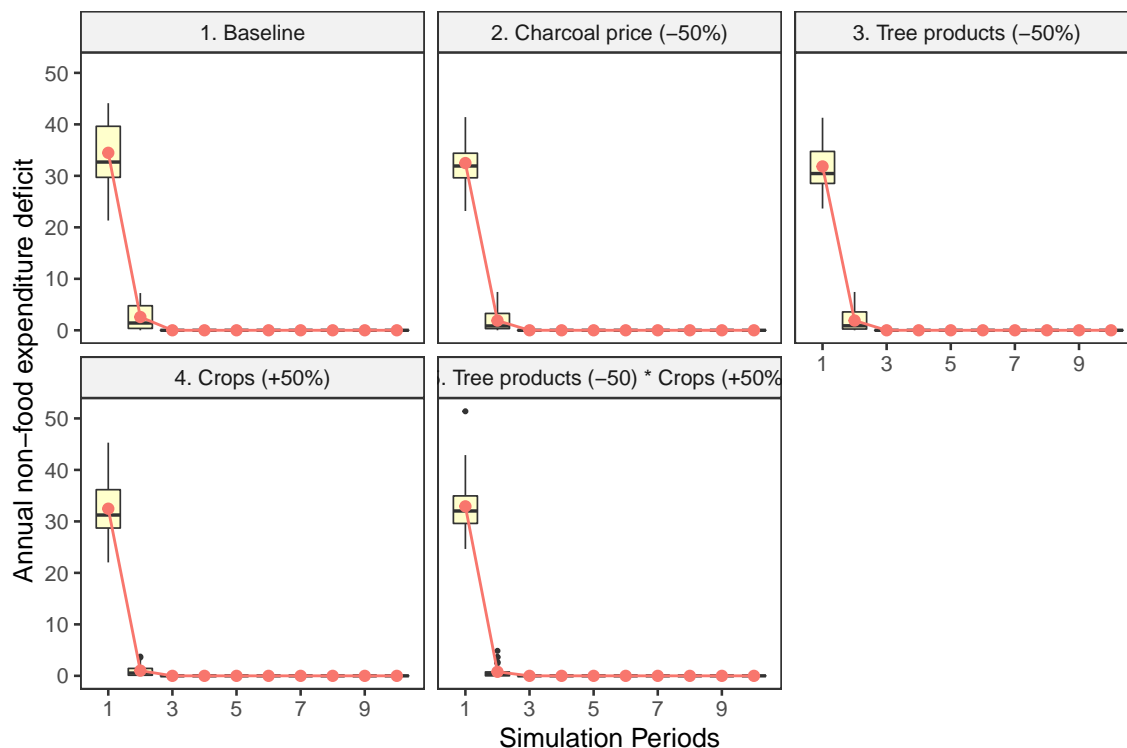


Figure 5.30: Annual non-food expenditure deficit

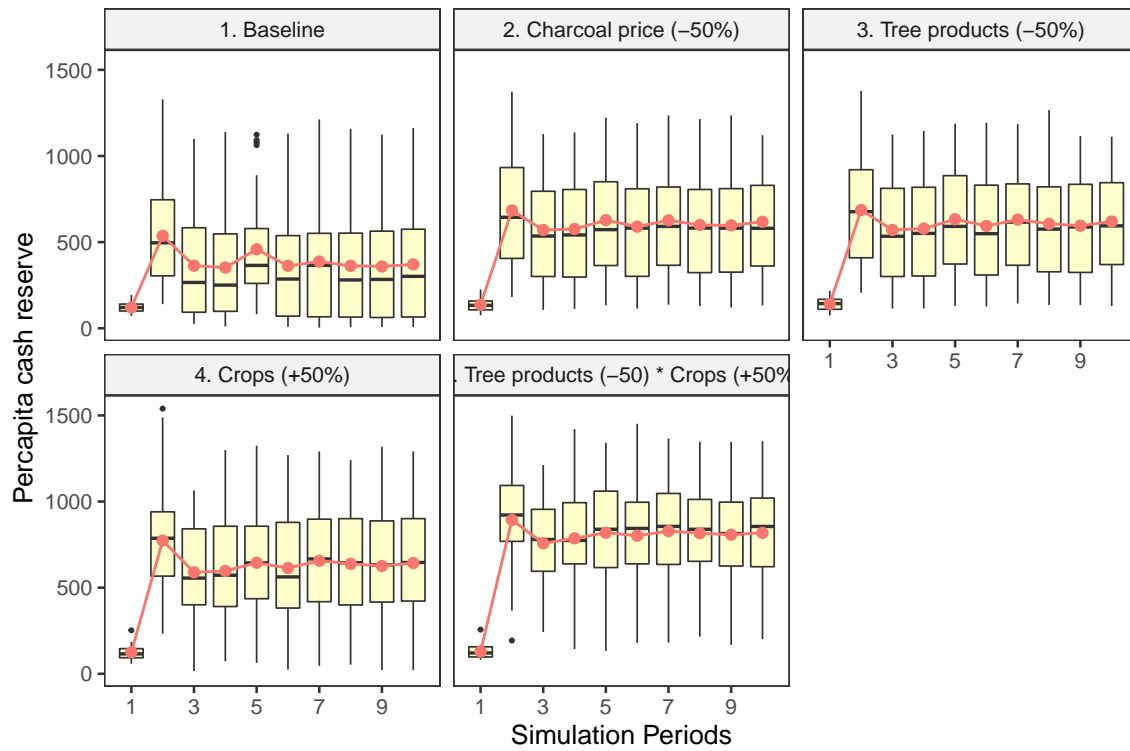


Figure 5.31: Average annual percapita cash reserve

Chapter 6

Discussion

Chapter objectives

- *Discussing the main findings of the study*
 - *Discussing results from econometric analysis*
 - *Discussing results from simulation experiments*
-

6.1 *Farmers' choice of ex-ante and ex-post measures*

What are the drivers of choice?

In the first part of this thesis drivers of farmers' ex-ante and ex-post strategy choices for climate variability-induced shocks is disentangled by blending LPCA and MVP regression. The LPCA results indicate that crop management activities such as planting stress resistant crops and varieties, early planting, increasing seed rate and soil and water conservation practices are the dominant ex-ante measures for climate-induced shocks. Whereas, selling livestock, selling assets, reducing consumption, borrowing and replanting are the dominant ex-post measures.

The MVP regression result reveals human capital of the household, mainly gender and education of the household head, significantly determine farmers' choice of ex-ante and ex-post risk management and coping measures for drought and pests. Soil and water conservation activities are highly labour-intensive and are usually done by male laborers. Similarly, (Bedeke et al. 2019) and (Wossen et al. 2018) found that male headed households are more likely to adopt ex-ante measures such as drought resistant varieties, chemical fertilizer application and soil and water conservation activities. Gender is also a significant factor determining farmers choice of ex-post drought coping measures. However, the effect of gender on choice of measures is different for

different values of TLU. Female headed smallholders have relatively lower asset base than their male counterparts. This is in line with the results obtained in (Wossen et al. 2018). Such resource limitation has adverse effects on the livelihoods of female headed farm households. One of such adverse effects is lower confidence (attributed to no or inadequate collateral) in the eyes of creditors – both personal and institutional creditors.

The role of rural institutions and social networks to risk management and coping strategy efforts of farmers has been well established (Wuepper et al. 2018). Results show that members of *iddir* plant drought tolerant varieties and plant early more often than non-members do. This is perhaps due to information sharing among members of *iddir*. *Iddir* is very important rural institution which provide farmers with access to information and support. Same results were found from Ethiopia and Tanzania in (Dercon et al. 2006). *Iddir* has also a significant effect in the farmers choice of ex-post measures. Members of *iddir* have relatively better access to borrow money, food or other items than non-members and are less likely to sell livestock to cope drought.

In a rural society where farmers have low resource endowments and agriculture is highly climate sensitive, strong social networks are a safety net to circumvent the adverse effects of shocks both before and after their occurrence (Wuepper, Yesigat Ayenew, and Sauer 2018; Caeyers and Dercon 2012). This findings of this research reveled that having friends or relatives in leadership position help farmers prepare for the possible occurrence of drought ahead through shared knowledge or inputs. In connection with this (Caeyers and Dercon 2012) found that farmers who have close associates in official position have a 12% more chance of getting free food.

Farmers' resilience to shocks is highly correlated with their resource endowments (Asrat and Simane 2018). Similarly, it has been found that livestock ownership is associated with increasing seed rate and engage in off-farm activities as an ex-ante hailstorm strategy. Whereas, larger farm size is associated with planting drought tolerant crops, replanting and consumption smoothing. Besides farmers non-food expenditure is a significant driver for farmers choice of measures to deal with climate variability induced shocks.

Findings show that farmers who took training and counselling on adaptation to climate variability are more resilient to climate variability induced shocks This is quite unequivocal as farmers who have better knowledge on how to deal with shocks before and after the occurrence are expected to perform well than others. Farmers knowledge and access to extension services are very important in determining farmers choice of adaptation measures, similar results in this regard has been found by (Asfaw et al. 2018).

Farmers shock experience and expectation has a crucial role in the choice of ex-ante adaptation measures for climate variability induced shocks. Besides the experience and knowledge farmers acquire from past shocks provides them with feedback to their coping measures choices in the aftershock.

The MVP model result reveals that farmers in drought, hailstorm and pest and crop

disease frequent areas are more likely to plant stress tolerant varieties and engage in soil and water conservation activities as ex-ante adaptation measures to prevent or minimize the adverse effects of shocks. Moreover, the correlation coefficient matrix reveals these measures as complementary measures with a very strong correlation coefficient of their respective error term. The complementarity of adoption of these measures enables farmers to curb short run shock surprises via planting stress tolerant crops and long run resilience through preserving water and soil fertility via soil and water conservation activities. Furthermore, farmers who have future shock expectation are more likely to choose farm management practices such as planting stress tolerant crops; planting stress tolerant varieties and engaging in soil and water conservation activities.

Frequency of climate variability induced shocks has also a significant effect in farmers choice of ex-post measures. Findings of the research show that farmers in shock prone areas choose to sale livestock to cope to climate variability induced shocks. Livestock is an important agricultural asset to smallholders in Ethiopia which provide farmers with different means of livelihood. More importantly, livestock are capital assets of farmers which provide inputs to agricultural production such as draft power and transportation. It is sensible that subsequent climate variability induced shocks deplete farmers livestock through death attributed to water stress; killing them for their meat or by selling them for cash to buy food. In other words, farmers from less drought frequent areas are less likely to sell livestock to cope with the pressure in the aftermath of drought. Findings of this research show that farmers living in shock frequent areas are less likely to reduce their consumption. However, farmers in these areas with higher expectations in the frequency of shock occurrence in the future tend to reduce their consumption and sell other assets instead of livestock. This suggests farmers with frequent shock experience and high expectations of future shocks tend to reserve their productive assets to save their future and try to live by other less destructive means to escape the short run effect of climate variability induced shocks on their livelihood. Furthermore, both LPCA and MVP post estimation results consistently indicate that there is high complementarity and few substitutability of measures chosen by farmers. Complementarity is strong in both ex-ante and ex-post measures while competitiveness is strongly prevalent in ex-post measures. This shows that robustness of interventions should involve multiple measures and there is no single best strategy that fits all farmers.

LPCA also shows the correlation between farmer ex-ante and ex-post strategy choices over the past ten years. Findings of this research show that farmers invest more on ex-post measures than ex-ante measures. This is perhaps attributed to the low resource settings smallholders have. Being resource constrained puts farmers in a position to choose the more cost-effective method to deal with climate variability induced shocks. They could invest either in ex-ante, ex-post or both and the measures chosen in any of the above cases, however, must be affordable to the farmer. With poor resource setting of smallholder farmers, they may not be able to choose the most effective strategy and thus will be forced to settle for compromises to optimize under the new set of options they have.

6.2 *Ex-ante planning for shocks and the role of small-scale agroforestry*

In the second part of the thesis a farm decision model representing smallholder farmers in the Ethiopia's Upper Nile Basin is developed to simulate how they would change their farm level decisions with shocks and price variability in the future and to measure the effect on their income thereof. Results show that agents in the model would change their land-use decisions based on the type of shock they are facing - both before the shock as part of their ex-ante planning, and after the shock as their ex-post coping measures.

What is the effect of investment on acacia on agents' land-use decisions and their discretionary income?

Scenarios with and without investment in acacia are compared first to show the contribution of investment in acacia to income and land-use shares. It has been found from simulation results that acacia takes more than 40% of land-use share in the area per year on average. This has reduced the share of annual crops simultaneously. Moreover, it has been found that land-use share of acacia increases with farm size. This is plausible as agents' with smaller farm sizes has to allocate some part of their land to produce food crops to fulfill their minimum consumption requirements. Results also show that with investment in acacia agents would get 8% higher percapita discretionary income each year on average. As a result, agents are able to fulfill the food and non-food expenditures better with acacia than without acacia, except in the first couple of simulation periods for few agents who have smaller farm sizes.

In their research (Nigussie et al. 2020) showed that acacia-based *taungya* system has relatively higher profitability in the study area than other cropping alternatives. Similar results were found by (Ajayi et al. 2009) in Zambia where agroforestry practices are more profitable specially if the alternative options are growing unfertilized crops - which is similar to the case in the study area of this research attributed to acidity of the soil (Berihun et al. 2019). Nigussie et al. (2020) also showed that farmers with larger farm size prefer investment in woodlots than those who have smaller farm sizes attributed to lower liquidity of standing trees. These results are in line with the simulation experiment results found in this study.

The amount of agents' annual discretionary income depends on off-farm income in addition to farm income. Off-farm income, on the other hand, depends on the amount of excess labor available for the agent after all farm activities are covered, and also on off-farm work availability in the area. In this connection, one of the advantages of acacia is its low labor requirement specially in the second, third and fourth years of the standing tree. This provides agents with extra excess labor capacity compared to the case where there is no investment on acacia. This excess capacity is the source of off-farm work for agents and thus a source of extra income. Moreover, as discussed in chapter four, acacia also brings employment opportunities for farmers in the study area throughout the year starting from seedling preparation to charcoal making.

One of the challenges during model implementation was data gap on the availability of off-farm work in the area. The assumption of off-farm labor availability as a percentage of excess labor of an agent in the model determines the amount of off-farm income they get. If the appropriate value is not considered, the assumed value of off-farm labor availability will underestimate or overestimate the amount of discretionary income agent would get, which in turn underestimates or overestimates the effect of investment in acacia on discretionary income. Higher value, for example, would give agents easy money. This has been shown in the uncertainty analysis during model validation in chapter four. During the interactive model validation sessions, experts were provided with options and asked to choose how much they would think is a relatively appropriate value in terms of percentage. Besides, they were asked to suggest their own figures. Based on the results almost all of the experts opted for a value somewhere around 10% of excess labor which is implemented in the model accordingly. To this effect the value of discretionary income obtained from simulation results can be considered as adequate. However, results could be sharpened more with detailed data on off-farm work availability in the area.

What is the effect of shocks on agents' land-use decisions and their discretionary income? and what is the role of ex-ante planning?

The effect of shocks on land-use decisions is observed in an *ex-post facto* basis. To have a direct effect on land-use the shock has to either force agents to change land-use decisions in the same period or make them adjust their decisions in future periods based on assumed expectation formation. The frequent and intense crop and tree diseases in the area - potato late blight and acacia seedling disease are introduced as shocks in the model to see the effect on agents' livelihoods. Since it is assumed in the model that agents have constant expectations, late blight doesn't affect land-use shares like acacia seedling disease. Simulation results also show that land-use share of acacia decreases against crops in scenarios where acacia seedling disease occurs or in the scenario where both potato late blight and acacia seedling disease occur in the same period.

Unlike in the case of shocks, agents' ex-ante decision to plan for shocks may directly affect land-use shares of trees and crops irrespective of assumption on expectation formation. Changes in land-use shares in such cases is perhaps attributed to agents' initial endowments and their respective affordable adaptation strategies for future shocks. This, for example, might involve growing more of one crop than the other or more trees than crops, or vice versa. Simulation results show that the effect of ex-ante planning on land-use shares is very small. This is perhaps related to small farm size agents have on average which limits their option to apply diversified cropping plans. The flexibility is even very low when agents are expected to fulfill their minimum food consumption from own production. Even though the magnitude of ex-ante planning effect on land-use shares is small, agents prefer to plant trees than crops as part of their ex-ante planning for shocks. This is in line with the results obtained in the econometric analysis.

Both ex-ante plannings for shocks and shocks' occurrence indirectly affect discretionary

income through crops/trees grown and the respective changes in yields. The percentage change in percapita discretionary income from the baseline is compared for all shock types and with and without ex-ante planning. Simulation results show that potato late blight induced yield loss reduces discretionary income of agents by almost 60% in the year they occur whereas acacia seedling disease reduces it by 30%. Potato late blight and acacia seedling disease occurring in the same year reduce discretionary income by more than 50%.

How responsive are agents' to long run expected price shocks?

The second simulation experiment examines sustainability of acacia in the presence of long run expected price shocks. Four scenarios are designed to capture price shocks in the future and the results are compared with the baseline to examine the effect on agents' discretionary income and land use decisions.

Simulation results show that agents are highly responsive to changes in expected prices in the long run except for the expected price of bamboo. Figure 6.1 summarizes the effect of changes in expected prices of crops and tree products on aggregated land-use. In cases where there is a decrease in the expected price of charcoal or an increase in the expected price of crops or both, results show that agents will go back to potatoes and wheat-dominated production system instead of acacia-dominated production system as in the baseline. The symmetric shape of the area plot in Figure 6.1 shows the substitutability between crops and trees.

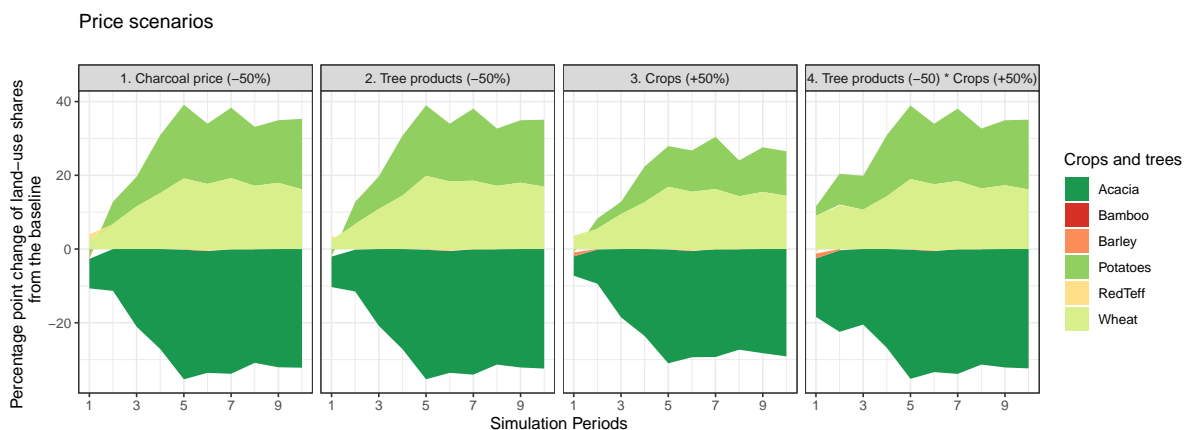


Figure 6.1: Percentage point difference of land-use share for all price scenarios from the baseline

Similar results have been found by (Nigussie et al. 2020) on the effect of extreme price variability on land use decisions of farmers in the study area. Their findings show that extreme price fluctuations in the future could reduce profitability of investment in acacia and forces farmers to shift back to annual crops instead of woodlots.

Price shocks have a direct effect on discretionary income of agents. Simulation results shows that income effect of changes in expected price is higher for crops than tree

products. A 50% increase in the expected price of crops increases average annual discretionary income of agents by more than 25%. Similar figures were found in the scenario where expected prices of crops increase by 50% and expected price of tree products decrease by 50% simultaneously.

Chapter 7

Conclusions

Chapter objectives

- *Making concluding remarks based on the results obtained from the study*
 - *Pinpointing policy implications based on the results of the study and gaps for further research*
-

Climate variability-induced and other covariate shocks have been posing serious problems to smallholder farmers' welfare in Ethiopia both in the short run via reducing production and increasing input and output prices and in the long run by depleting productive farm assets leading to a poverty trap. However, the impact of these shocks on farmers' welfare depends on the measures farmers use to deal with them before and after their occurrence and is, therefore, farmer-specific. Scientific assessment intended to support the design of successful and robust climate adaptation strategies should take the heterogeneity of farming households into account - failure to do so results in unequal treatment of farmers and may lead to maladaptation. In this connection, this study integrates econometric and farm-level simulation analyses to examine smallholder farmer choices of ex-ante adaptation and ex-post coping measures to climate variability-induced and other covariate shocks in Ethiopia, with a special focus on the role of investment on small-scale agroforestry.

The first objective of this study is to learn farmers' current behavioral choices of ex-ante adaptation and ex-post coping measures to deal with climate variability-induced and other covariate shocks and examine farmer-specific drivers of choice. This is aimed at answering - *How do farmers deal with shocks currently?* question. For this purpose, the study integrates LPCA and MVP analysis to disentangle farmer-specific determinants of the choice of ex-ante and ex-post measures for drought, hailstorm, pests and crop disease in Ethiopia. Dimensionality reduction of binary data using LPCA identifies dominant ex-ante and ex-post measures of farmers for climate variability induced shocks. Planting stress resistant crops and varieties, early planting,

increasing seed rate and soil and water conservation practices are the dominant ex-ante measures. Whereas, selling livestock, selling assets, reducing consumption, borrowing and replanting are the dominant ex-post measures. This suggests that adaptation to climate variability-induced shocks should focus on crop and land management activities. And, building households' asset base will boost farmers' resilience to these shocks.

Farmers' interdependent adoption decisions of adaptation and coping measures are captured using MVP regression models to examine the drivers of choice. MVP results show that several factors determine farmers' choice of adaptation and coping measures. Gender, knowledge and experience, participation in rural institutions, social networks, resource endowments and their shock experience and expectation are the major drivers of farmers' choices of ex-ante adaptation and ex-post coping measures. This suggests that the choice of strategies by smallholder farmers to deal with climate variability-induced shocks is highly idiosyncratic and depends on their socioeconomic settings, their experience and knowledge and their interactions with the environment. As a result, robust climate adaptation and mitigation interventions should take this heterogeneity into account.

Results from both LPCA and MVP show that most of measures farmers choose are complementary measures. This implies that there is no single best strategy that works for all farmers, instead farmers use multiple adaptation and coping measures. Complementarity of measures is stronger in ex-ante measures than ex-post measures. Farmers invest more on ex-post measures than ex-ante measures. And, those who invest on tree perennials as ex-ante drought measure are less likely to use severe measures such as selling livestock and other assets in the aftershock.

This study's second and third objectives focus on *How farmers would behave to deal with shocks in future circumstances?* The econometric analysis in the first part of the thesis establishes a descriptive analysis of farmers' behavioral responses to climate variability induced and other covariate shocks. This captures the behavior of farmers in the status quo. However, it does not tell us much about how farmers would behave in different future circumstances, especially with climate and price variability. This requires a prescriptive and descriptive approach with a detailed investigation of farmers' behavior down to the plot level. To achieve this objective, the second part of the study applies household level micro-simulation to analyze ex-ante planning and ex-post responses to future climate and price variability with a particular focus on the role of smallholders' investment in woodlot perennials to their livelihoods. The agent-based simulation package - Mathematical Programming-based Multi-Agent Systems (MPMAS) is used for this purpose to capture production, consumption and investment decisions at the farm household level. A farm decision model representing smallholder farmers in the Upper Nile Basin in Ethiopia is developed accordingly. The farmers in the area are known for their integrated crop-livestock system and a unique *Acacia Dicurrens* based *Taungya* system.

Two simulation experiments were designed to quantify the effects of shocks and price variability on agents' livelihoods. The High Performance Computing platform in Baden

Wurttemberg (bwHPC) is used to run simulation experiments for this study. The first simulation experiment aims at achieving two sub-objectives. The first sub-objective is measuring the contribution of investment in acacia-based woodlots on farmers' land-use decisions and their discretionary income. Simulation results show that acacia accounts for more than 40% land-use shares in the area on-average in each year. The expansion of acacia-based agroforestry system in the study area brings farmers with additional benefits in terms of increased per capita discretionary income and helps them withdraw from failure to fulfill their food and essential non-food expenditure.

The second sub-objective measures the effects of shocks on agents' livelihoods and the effectiveness of ex-ante planning to curb the adverse effects of these shocks. The frequent and intense crop and tree diseases in the area - potato late blight and acacia seedling disease are introduced as shocks in the model. Simulation results show that both potato late blight and acacia seedling disease reduce annual per capita discretionary income significantly and forcing some resource poor agents to fail to fulfill minimum non-food expenditure. The trade-off in agents' land-use decisions between trees and crops by agents show that they prefer to plant trees than crops as an ex-ante planning strategy for shocks.

The second simulation experiment aims at examining the effect of long-run expected price changes, mainly on land-use decisions of agents in the model. Four future price scenarios are designed and the results are compared with the baseline to examine the effect on agents' discretionary income and land use decisions. The purpose of this simulation experiment is to see if there is a deviance from croplands to woodlots and vice versa based on long-run changes in expected prices. Simulation results show that agents are highly responsive to changes in expected prices in the long run, except for the expected price of bamboo. In cases where there is a decrease in the expected price of charcoal or an increase in the expected price of crops or both, results show that agents will go back to potatoes and wheat-dominated production system instead of the acacia-dominated production system as in the baseline.

Policy implications and way forward

Based on the findings of this study, the following policy implications could be drawn as takeaway messages for policymakers.

- Supporting farmer adaptation to climate variability induced shocks should focus on policy interventions related to crop and land management activities.
- Policy interventions building the household asset base will boost farmers coping ability and resilience to shocks.
- Robust climate adaptation and mitigation interventions should take the heterogeneity of farmers into account.
- Investment in woodlot perennials is a crucial adaptation strategy for smallholder farmers. Particularly, both econometrics and farm-level simulation analyses show

the importance of planting trees as a crucial adaptation strategy.

In addition to the findings and policy implications obtained, this study also helped identify important gaps for further research. The following are some of the areas of future research:

- It has been understood from the interactive validation sessions that the soil fertility improvement role of acacia dicurrens in the study area might outweigh the financial benefits. In other words, farmers might not want to shift from woodlots to croplands (or the magnitude of the shift might be different) even if the financial benefits are higher in the later. So, a financial analysis alone might not comprehensively show the effect of investment in acacia on farmers' livelihoods. To this effect, the contribution of acacia to the soil as a leguminous plant and the resultant improvement in crop yield after subsequent cycles of acacia should be taken in to account. This can be methodologically captured using a soil dynamics feature in the farm decision model once the yield effect of improvement in the soil is known. The soil dynamics feature in the model is already implemented. Yet, the yield effects are set to be constant at the current status of the model irrespective of multiple cycles of acacia. This calls for further research and sharpens the effect of investment in acacia on agents in the model.
- Another important feature of the model which needs more expansion is livestock production. The role of livestock to farmers' livelihood in the area is well established. Even though the income from livestock in the model is validated, the type of livestock the agents are keeping and the number of years they are keeping them in the model is a bit different from what is happening in reality. Agents only keep cows and chickens, and they only keep them for one year. As livestock is an important adaptation and coping measure for farmers, among other things, a detailed representation of livestock production activities and constraints backed by detailed data could improve the results of the model further.
- Furthermore, the importance of off-farm work as an adaptation and coping measure should be investigated alongside the role of investment in acacia dicurrens which also provides with extra surplus labor compared to the crop-based production systems.
- More up-to-date data on adaptation and coping strategy choices of farmers would also help us have the state of the art knowledge on how farmers deal with climate variability-induced shocks.

Appendix A

The farm decision model

Objective function

Agents optimize expected cash surplus only after ensuring current and future minimum consumption needs are fulfilled and adequate precaution is taken to shocks.

$$Max : \left(\sum_t Cash\ Surplus - \sum_{t=0} CD^{cp} - \sum_{t>0} \bar{C}D^{cp} - \sum_{t,s} CD^{ep} \right)$$

Where CD is consumption shortage; t is time (T planning periods); s is shocks; cp is current period ($t = 0$); and ep is future periods ($0 < t \leq T$)

Detailed expansion of components of the objective function are provided in equations (A.39) to (A.46)

Crop Production

Land balances

Total available land (FS) is exhaustively used for one or more of the following activities:
- grow crop, grow pasture or grow perennials

$$\sum_c X_{land}^{transfer} + \sum_c X_{grow}^{pasture} + \sum_c X_{grow}^{perennials} = FS$$

For crops only, land in use balance constraint is defined as.

$$\sum_c X_{land}^{transfer} - \sum_c X_{grow}^{crops} = 0$$

Transfer land is introduced because of rotation constraints in crops. For perennials, land in use balance constraint is defined as:

$$\sum_l X_{perennialland}^{transfer} - \sum_w X_{maintain}^{plantation} = 0$$

Maintain plantation activity at period t refers to having a tree plantation w of age a in period t

Crop rotation

Potatoes are rotated every other year in dega AEZ. And, in kola hot pepper is rotated every other year.

$$Rotation\ limit = \frac{1}{2}$$

$$\sum_{rc} X_{grow}^{rotatedcrops} - 0.5 * X_{land}^{transfer} \leq 0$$

Labor balance

Labor capacity

Use of family labor cannot exceed available labor in the household (LC) at any time t . Where lt is a set of labor types.

$$lt = smallchildlabor, childlabor, malelabor, femalelabor, seniorlabor$$

Therefore, the labour capacity constraint is defined as:

$$\sum_{lt} X_{use}^{familylabor} \leq 24 * LC$$

Where 24 is the time division of the year. 1 *time division* = 2 *weeks* and, labour is measured in person days

Labor balance without herding

Labor use types (lut) are a set of farming activities

$$Lut = preparation, weeding, harvesting, herding, processing, off - farm$$

For all labor use types except herding, the labor balance constraint is defined as follows:

$$\begin{aligned} & \sum_{c, lut} X_{grow}^{crops} * L_{dd}^{crop} + \sum_p X_{maintain}^{perennials} * (L_{dd}^{perennials} + L_{dd}^{intercropping}) \\ & + \sum_p X_{cutdown}^{perennials} * L_{dd}^{cutdown} + \sum_l X_{consume}^{ownprocessedlivestock} * L_{dd}^{processlivestock\ products} \\ & + \sum_l X_{sell}^{livestock} * L_{dd}^{processlivestock\ products} - \sum_{lt} X_{use}^{familylabor} \leq 0 \end{aligned}$$

Herding labor balance

At any time t in the planning period the labor used for herding livestock must be less than or equal to the total amount of labor available in the household

$$\sum_{l,t} X_{keep}^{livestock} * L_{dd}^{herding} - \sum_{lt} X_{use}^{familylabor} \leq 0$$

Herding labor balance FSE ($t = T$)

At the end of the planning period the labor used for herding livestock must be less than or equal to the total amount of labor available in the household and hired labor.

$$\sum_{l,t} X_{keep}^{livestockFSE} * L_{dd}^{herdingFSE} - \sum_{lt,t} X_{use}^{familylabor} - \sum_t X_{hire}^{labor} * p_{wage}^{labor} \leq 0$$

Input balance

Agents do not buy inputs i of crop production in excess of demand. Bought inputs of crop production are fertilizer (DAP, UREA) and improved seeds

$$\sum_c X_{grow}^{crops} * i_{dd}^{crops} - \sum_i X_{buy}^{inputs} \leq 0$$

Food storage

Agents store food to smooth consumption. Maximum food storage time is 2 years (lifetime). Stored food is, therefore, an asset. Food storage constraints of agents will be introduced first as they are important component of product balances.

Storablecropssc = maize, wheat, barley, white teff, red teff, hot pepper

Start of period storage balance $1 < t < T$ & $a = 1$

In future periods except the final period, the total amount of food kept in storage, taken from storage and reserved storage for shocks should not be bigger than the total amount of food stored in the previous period.

$$\sum_{sc,a,t} X_{keepin}^{storage} + \sum_{sc,a,t} X_{takefrom}^{storage} + \sum_{sc,a,t} X_{reserveforshock}^{storage} - \sum_{sc,t-1} X_{interedinto}^{storage} \leq 0$$

Start of period storage balance $1 < t < T$ & $a < 2$

In future periods except the final period and for year of storage lifetime, the total amount of food kept in storage, taken from storage and reserved storage for shocks

should not be bigger than the total amount of food kept in storage in the previous period.

$$\sum_{sc,a,t} X_{keepin}^{storage} + \sum_{sc,a,t} X_{takefrom}^{storage} + \sum_{sc,a,t} X_{reserveforshock}^{storage} - \sum_{sc,a-1,t-1} X_{keepin}^{storage} \leq 0$$

Start of period storage balance $1 < t < T$ & $a = 2$

In future periods except the final period and for year of storage life time ($a = 2$), the total amount of food taken from storage should not be bigger than the total amount of food kept in the previous period.

$$\sum_{sc,a,t} X_{takefrom}^{storage} - \sum_{sc,a-1,t-1} X_{keepin}^{storage} \leq 0$$

Start of period storage balance $t = 1$ & $a > 0$

At $t = 1$, the total amount of food kept in storage, taken from storage and reserved storage for shocks should not be bigger than the total amount of food stored at the end of the previous period ($SF_{t=0}$).

$$\sum_{sc,a,t} X_{keepin}^{storage} + \sum_{sc,a,t} X_{takefrom}^{storage} + \sum_{sc,a,t} X_{reserveforshock}^{storage} \leq SF_{t=0}$$

Start of period storage balance $t = 1$ & $a = 2$

At $t = 1$, the total amount of food taken from storage should not be bigger than the total amount of food stored at the end of the previous period ($SF_{t=0}$) aged the maximum lifetime.

$$\sum_{sc,a,t} X_{takefrom}^{storage} \leq SF_{t=0,a=2}$$

Reserve for shock storage balance $t < T$

For all future periods except the last period, taking from storage times the likelihood of shock occurrence must not be bigger than the total amount of reserved food storage for shocks.

$$Pr_s * \sum_{s,sc,a,t} X_{shocktakefrom}^{storage} - \sum_{sc,a,t} X_{reserveforshock}^{storage} \leq 0$$

Start of period reserve for shock storage balance $1 < t < T$

For all future periods except the first and the last period and for all storage ages, the total amount of food taken from storage during shock period t must not be bigger than the total amount of food taken into storage in the previous year.

$$\sum_{s,sc,a,t} X_{shocktakefrom}^{storage} - \sum_{sc,a-1,t-1} X_{keepin}^{storage} \leq 0$$

Start of period reserve for shock storage balance $1 < t < T$

For all future periods except the first and the last period and for the first year of storage, the total amount of food taken from storage during shock period t must not be bigger than the total amount of food entered storage in the previous year.

$$\sum_{s,sc,a,t} X_{shocktakefrom}^{storage} - \sum_{sc,t-1} X_{interedinto}^{storage} \leq 0$$

Final static equilibrium storage balances

Transition to FSE storage balance $t=T$

In the final period the total amount of food entered and kept in the previous period should not be less than the amount of reserve storage for shocks.

$$\sum_{sc,t} X_{reserveforshock}^{storageFSE} - \sum_{sc,a,t-1} X_{keepin}^{storage} - \sum_{sc,t-1} X_{interedinto}^{storage} \leq 0$$

Storage balance FSE $t=T$

In the final period the total amount of food entered should not be less than the amount of reserve storage for shocks.

$$\sum_{sc,t} X_{reserveforshock}^{storageFSE} - \sum_{sc,t} X_{interedinto}^{storageFSE} \leq 0$$

Reserve for shock storage balance FSE $t=T$

In the final period taking from storage times the likelihood of shock occurrence must not be bigger than the total amount of reserved food storage for shocks.

$$Pr_s * \sum_{s,sc,a,t} X_{shocktakefrom}^{storageFSE} - \sum_{sc,a,t} X_{reserveforshock}^{storageFSE} \leq 0$$

Product balances

Start of period in $[1 < t < T]$

At the start of each period (except for the first and the last period), the total amount of crops sold in the previous year (sole cropping and intercropping with perennials) and total consumption from own production should not be bigger than the total amount of non-stored harvest at time $t - 1$ and total harvest taken from storage at t

$ic = tef f, potatoes, barley, wheat, grass (pasture)$

$Storablecrops = maize, wheat, barley, redteff, whiteteff, hotpepper$

$$\sum_{c,t} X_{consume}^{ownproduction} + \sum_{c,t-1} X_{sell}^{crops} - \sum_{c,t} X_{takefrom}^{storage} - \sum_{c,t-1} X_{nonstored}^{crops} \leq 0$$

End of period in $[t = T, T]$

At the end of each period except the last period and one period before the last period, the total amount of crops produced (sole cropping, double cropping and intercropping with perennials) is either entered storage or not.

$Double\ cropping = barley\ after\ potatoes, in\ Dega\ AEZ$

$$\begin{aligned} & \sum_{c,t} X_{nonstored}^{crops} + \sum_{c,t} X_{interedinto}^{storage} - \sum_c X_{grow}^{crops} * y_{yield}^{crops} \\ & - \sum_c X_{grow}^{doublecropped} * y_{yield}^{doublecropped} - \sum_p X_{maintain}^{perennials} * y_{yield}^{intercropped\ crops} \leq 0 \end{aligned}$$

Harvest balance at $(t=1) = (year = 0)$

The amount of harvest at $t=1$ should not be bigger than what was planted in the year, if only planted. This is the possibility (potential) harvest in the beginning of the planning period. It is the result of the decisions taken before (no in the current setting of the model).

$$\sum_c X_{harvest}^{year=0} = \begin{cases} \sum_{c,t-1} X_{grow}^{crops} & , \text{ if grown} \\ 0 & , \text{ if not grown} \end{cases}$$

Product balance at $t=1 = (end\ of\ year = 0)$

At the end of each period except the last period and one period before the last period, the total amount of crops produced (sole cropping, double cropping and intercropping with perennials) is either entered storage or not.

$$\begin{aligned} & \sum_{c,t-1} X_{nonstored}^{crops} + \sum_{c,t-1} X_{interedinto}^{storage} - \sum_{c,t} X_{grow}^{crops} * y_{yield}^{crops} \\ & - \sum_{c,t} X_{grow}^{doublecropped} * y_{yield}^{doublecropped} - \sum_{p,t,a=0} X_{maintain}^{perennials} * y_{yield}^{intercropped crops} \leq 0 \end{aligned}$$

Product balance at $t=1$ (*start of period*)

At the beginning of period 1 the total amount of harvest sold and consumed in the agent's household must not be bigger than the total sum of stored and non-stored harvest in the previous period ($period = 0$).

$$\sum_{c,t} X_{sell}^{harvest year 0} + \sum_{c,t} X_{consume}^{ownproduce} - \sum_{c,t-1} X_{nonstored}^{crops} - \sum_{c,t-1} X_{interedinto}^{storage} \leq 0$$

Inter cropping harvest balance at $t=1$ (*year = 0*)

Total number of plots of possible harvest of crops intercropped with perennials before the start of the planning period must not be bigger than perennials established in the previous period, if established (planted).

$$\sum_{c,t} X_{harvest}^{tXharvestintercroppingyear=0} = \begin{cases} \sum_{p,t=1,a=0} X_{maintain}^{perennials} & , \text{ if planted} \\ 0 & , \text{ if not planted} \end{cases}$$

Shock product balance at $[1 < t < T]$

For all future periods except the last period, agents' product balance is also considerate of shocks. In these periods total amount of harvest from sole cropping, double cropping and intercropping in the previous period ($t - 1$) and harvest taken from storage at t should be greater than or equal to the amount of harvest sold in the previous period ($t - 1$) and amount consumed during shock period t $wcyield$ is worst case yield expected in time of shocks and s is a set of shocks.

$S = drought, hotpepperdisease, wheatdisease, maizedisease, teffdisease, potatodisease$

$$\begin{aligned} & \sum_{c,s,t} X_{shocksell}^{crops} + \sum_{c,s,t} X_{shockconsume}^{ownproduce} \\ & - \sum_{c,s,t} X_{shocktakefrom}^{storage} - \sum_{c,t-1} X_{grow}^{crops} * y_{wcyield}^{crops} \\ & - \sum_{c,t-1} X_{grow}^{doublecropped} * y_{wcyield}^{doublecropped} - \sum_{p,t-1,a=0} X_{maintain}^{perennials} * y_{wcyield}^{intercropped crops} \leq 0 \end{aligned}$$

Final static equilibrium

End of period $[t=T-1]$

At the end of the previous period before the final period ($t = T - 1$) the total amount of crops produced (sole cropping, double cropping and intercropping with perennials) is greater than or equal to stored and non-stored harvest in the same period.

$$\begin{aligned} & \sum_{c,t} X_{nonstored}^{crops} + \sum_{c,t} X_{interedinto}^{storage} \\ & - \sum_{c,t} X_{grow}^{crops} * y_{yield}^{crops} - \sum_{c,t} X_{grow}^{doublecropped} * y_{yield}^{doublecropped} \\ & - \sum_{p,t,a=0} X_{maintain}^{perennials} * y_{yield}^{intercropped crops} \leq 0 \end{aligned}$$

Start of period $[t=T]$

In the final period whatever is not consumed at $t = T$ or sold at $t = T - 1$ should not be bigger than what has not been stored at $t = T - 1$. The notion here is agents do not store grains anymore.

$$\sum_{c,t-1} X_{sell}^{harvest year0} + \sum_{c,t} X_{consume}^{ownproduce} - \sum_{c,t-1} X_{nonstored}^{crops} \leq 0$$

Final static equilibrium $[t=T]$

In the final period the total amount of harvest sold, consumed at home and entered in to storage should not be bigger than the total amount of crops produced (sole cropping, double cropping and intercropping with perennials) and the reserved storage for shocks in the same period.

$$\begin{aligned} & \sum_{c,t} X_{sell}^{crops} + \sum_{c,t} X_{consume}^{ownproduce} + \sum_{c,t} X_{interedinto}^{storage} \\ & - \sum_{c,t} X_{shockreserve}^{storage} - \sum_{c,t} X_{grow}^{crops} * y_{yield}^{crops} \\ & - \sum_{c,t} X_{grow}^{doublecropped} * y_{yield}^{doublecropped} - \sum_{p,t,a=0} X_{maintain}^{perennials} * y_{yield}^{intercropped crops} \\ & \leq 0 \end{aligned}$$

Shock balance in FSE $[t=T]$

In the final period and in the case of shocks in $T - 1$, the total amount of harvest from sole cropping, double cropping and intercropping in the previous period and harvest

taken from storage at t should be greater than or equal to the amount of harvest sold in the and amount consumed.

$$\begin{aligned} & \sum_{c,s,t} X_{shocksell}^{cropsFSE} + \sum_{c,s,t} X_{shockconsume}^{ownproduce} \\ & - \sum_{c,s,t} X_{shocktakefrom}^{storageFSE} - \sum_{c,t} X_{grow}^{crops} * y_{wcyield}^{crops} \\ & - \sum_{c,t-1} X_{grow}^{doublecropped} * y_{wcyield}^{doublecropped} - \sum_{p,t,a=0} X_{maintain}^{perennials} * y_{wcyield}^{intercropped crops} \leq 0 \end{aligned}$$

Credit and savings

Credit limit

The total amount of loan an agent can get from different credit sources should not exceed the maximum amount allowed.

$$\sum_{cs,t} X_{take}^{loan} + \sum_{cs,t} X_{shockreservetake}^{loan} \leq CL_{cs}$$

CL is credit limit

cs is credit sources

cs = microfinance, moneylender, relatives

Loan repayment balance at $t=1$

At the end of $t=1$ the total amount of loan repaid, and the amount defaulted should be exactly equal to the amount of loan taken in the previous simulation period.

$$\sum_{cs,t} X_{repay}^{loan} + \sum_{cs,t} X_{defaulted}^{loanquantity} = \sum_{cs,t} X_{take}^{loan}$$

Existing deposit balance at $t=1$

At $t = 1$ the total amount of deposit available is equal to the amount of money deposited in the previous simulation period

$$X_{existing_t}^{deposit} = X_{existing_{t=1}}^{deposit}$$

Block access to credit after default at ($t=1 + 5th$)

Agents who default in the previous period are denied access to credit for the succeeding 5 years

$$\sum_{cs,t} X_{take}^{loan} + bigM * X_{Default}^{Dummy} = bigM + (-bigM) * \sum_{cs,t} X_{Defaulted}^{on}$$

$$X_{Default}^{Dummy} = \begin{cases} 1 & , \text{ if dafaulted} \\ 0 & , \text{ if not dafaulted} \end{cases}$$

bigM is large number

Require register default at ($t=1$)

$$\sum_{cs,t} X_{defaulted}^{loanquantity} - bigM * \sum_{cs,t} X_{Defaulted}^{on} \leq 0$$

Take loan reserve balance at ($t>1$)

In all future periods, where the previous period is a shock period, reserve loan during shocks is less than or equal to the probability of shock occurrence times the amount of loan taken during shocks.

$$Pr_s * \sum_{cs,s,t} X_{take}^{loan} - \sum_{cs,t} X_{shockreservetake}^{loan} \leq 0$$

Cash balances

Start of year cash balance at $t=1$

The cash balance in the first planning period: total costs of production, amount of cash transferred to the start of the next period, the amount of money withdrawn, cash deposited and loan repayment should not exceed the total revenue from sales and the cash reserve obtained from the previous period. Current market price is used at $t = 1$. *ETB* is the monetary unit.

$$\begin{aligned} & \sum_{i,t} X_{buy}^{inputs} * p_{market}^{inputprice} + \sum_{c,t-1} X_{consume}^{boughtcrops} * p_{market}^{boughtcrops} * p_{coefficient}^{consumption} + \\ & \sum_{l,t} X_{buy}^{livestock} * p_{market}^{boughtlivestock} * p_{buying}^{topup} + \sum_{l,t-1} X_{keep}^{livestock} * C_{keeplivestock}^{variablecost} + \\ & \sum_{l,t-1} X_{raise}^{livestock} * C_{raiselivestock}^{variablecost} + \sum_t X_{hire}^{labor} * p_{wage}^{labor} + \\ & \sum_t X_{hire}^{oxen} * p_{price}^{pairofoxenperday} + AIR * \sum_t X_{cashtransfer}^{startofnextyear} + \\ & \sum_{t-1} X_{withdrawcash}^{endofpreviousperiod} + \sum_{p,t} X_{maintain}^{perennials} * C_{maintainperennials}^{variablecost} + \end{aligned}$$

$$\begin{aligned}
& \sum_{p,t} X_{establish}^{perennials} * p_{price}^{seedling} * SD + X_{deposit_t}^{cash} + \frac{1}{AIF} * \sum_{cs,t} X_{repay}^{loan} * r_{interestrate}^{loan} - \\
& \sum_{c,t} X_{sell}^{cropharvest} * p_{market}^{cropprice} - \sum_{l,t-1} X_{sell}^{livestockproducts} * p_{market}^{livestockproducts} - \\
& \sum_{p,t} X_{sell}^{perennialproducts} * p_{pricecoefficient}^{AD} * p_{market}^{perennialproducts} - \sum_{l,t-1} X_{sell}^{livestockafterbirth} * p_{market}^{livestock} - \\
& \sum_{l,t-1} X_{sell}^{livestockatendofperiod} * p_{market}^{livestock} - \sum_{h,lp,t} X_{sell}^{hhlabor} * p_{wage}^{off-farm} - \\
& \left(\frac{1}{AIF} + r_{interestrate}^{deposit} * \frac{1}{AIF} \right) * X_{existing}^{deposit} \leq CR
\end{aligned}$$

$$p_{coefficient}^{consumption} = 1.7$$

$SD =$ Seedling density

$CR =$ agent financial cash reserves from previous period

$Att = 1, CR =$ initial liquidity the agent starts with

AIF is assumed inflation factor $AIR = 1.15$

$p_{pricecoefficient}^{AD}$ wighs perennial product prices

$p_{pricecoefficient}^{AD} = 1$, except acacia charcoal

$h =$ household labor type

$lp =$ is labor periods

r is interest rate

$\sum_{l,t} X_{buy}^{livestock}$ refers for both preferred and non-preferred ages

Start of year cash balance at $1 > t > T$

For future periods except the last period agent use expected prices instead of actual prices – because they don't know future prices. In each period costs of production, amount of cash transferred to the start of the next period, cash deposited, loan taken for shocks, normal loan taken and the amount of money withdrawn should not exceed the total revenue from sales, the cash transferred from the previous period, loan taken and cash deposited in the previous period.

$$\begin{aligned}
& \sum_{i,t} X_{buy}^{inputs} * ep_{market}^{inputprice} + \sum_{c,t-1} X_{consume}^{boughtcrops} * ep_{market}^{boughtcrops} * p_{coefficient}^{consumption} + \\
& \sum_{l,t} X_{buy}^{livestock} * ep_{market}^{boughtlivestock} * p_{buying}^{topup} + \sum_{l,t-1} X_{keep}^{livestock} * C_{keeplivestock}^{variablecost} +
\end{aligned}$$

$$\begin{aligned}
& \sum_{l,t-1} X_{raise}^{livestock} * C_{raiselivestock}^{variablecost} + \sum_t X_{hire}^{labor} * p_{wage}^{labor} + \\
& \sum_t X_{hire}^{oxen} * ep_{price}^{paairofoxenperday} + \sum_t X_{cashtransfer}^{startofnextyear} + \\
& \sum_{t-1} X_{withdrawcash}^{endofpreviousperiod} + \sum_{p,t} X_{maintain}^{perennials} * C_{maintainperennials}^{variablecost} + \\
& \sum_{p,t} X_{establish}^{perennials} * ep_{price}^{seedling} * SD + X_{deposit_t}^{cash} + SIF * \\
& \sum_{cs,t} X_{shocktake}^{loan} * r_{interestrate}^{deposit} + \sum_{cs,t-1} X_{take}^{loan} * (1 + DIF * r_{interestrate}^{loan}) - \\
& \sum_{c,t} X_{sell}^{cropharvest} * ep_{market}^{cropprice} - \sum_{l,t} X_{sell}^{livestockproducts} * ep_{market}^{livestockproducts} - \\
& \sum_{p,t} X_{sell}^{perennialproducts} * ep_{market}^{perennialproducts} - \sum_{l,t-1} X_{sell}^{livestockafterbirth} * ep_{market}^{livestock} - \\
& \sum_{l,t-1} X_{sell}^{livestockatendofperiod} * ep_{market}^{livestock} - \sum_{h,l,p,t} X_{sell}^{hhlabor} * p_{wage}^{off-farm} - \sum_{t-1} X_{cashtransfer}^{startofnextyear} - \\
& \sum_{cs,t} X_{take}^{loan} - \sum_{cs,t-1} X_{deposit}^{cash} * (1 + DIF * r_{interestrate}^{deposit}) \leq 0
\end{aligned}$$

T = planning horizon, ep = expected price, $SIF = 2$, is shock interest factor

Start of year shock cash balance at $1 > t > T$

For all future periods except the last period, in case of shock in the previous period, the net cash flow at the start of the year should at least be equal to household minimum consumption and worst-case cash top up. Cash inflows at (t) are: cash transferred from previous year, sales revenue from crops, livestock and perennial products in the previous period, and interest from deposit in the previous period plus off farm income, loan taken and cash consumption forgone in the current period (t) . Cash out flows at (t) are inputs of production (crop, livestock and perennials) at t including hired labor and oxen, shock time food expenditure at t and loan interest rate paid for credit taken in the previous year. The net cash flow ($cashinflow - cashoutflow$) should be greater than or equal to the minimum cash requirement of the agent plus a shock year cash to up.

$$\begin{aligned}
& \sum_{t-1} X_{cashtransfer}^{startofnextyear} + \sum_{c,t-1} X_{sell}^{cropharvest} * wp_{market}^{crop} + \\
& \sum_{s,t} X_{shockcashconsumption}^{forgone} + \sum_{l,t-1} X_{sell}^{livestock} * ep_{market}^{livestock} + \\
& \sum_{l,t-1} X_{sell}^{livestockafterbirth} * wp_{market}^{livestock} + \sum_{l,t-1} X_{sell}^{livestockatendofperiod} * wp_{market}^{livestock} +
\end{aligned}$$

$$\begin{aligned}
& \sum_{p,t} X_{maintain}^{perennials} * C_{maintainperennials}^{variablecost} * CNYID_{wc} \\
& + \sum_{p,t} X_{establish}^{perennials} * ep_{price}^{seedling} * SD * CNYID_{wc} + \\
& \sum_{h,l,p,t} X_{sell}^{hhlabor} * p_{wage}^{off-farm} + \sum_{cs,t} X_{take}^{loan} + (1 + r_{interestrate}^{deposit}) * X_{deposit_t}^{cash} - \\
& \sum_{i,t} X_{buy}^{inputs} * ep_{market}^{inputprice} * CNYID_{wc} - \sum_{c,s,t} X_{shockbuy}^{food} * wp_{market}^{crop} * p_{consumption}^{coefficient} - \\
& \sum_{l,t} X_{buy}^{livestock} * wp_{market}^{boughtlivestock} * p_{buying}^{topup} * CNYBL_{wc} * PSLPOCA - \\
& \sum_{l,t-1} X_{keep}^{livestock} * C_{keeplivestock}^{variablecost} * CNYID_{wc} - \\
& \sum_{l,t-1} X_{raise}^{livestock} * C_{raiselivestock}^{variablecost} * CNYID_{wc} \\
& - \sum_{p,t-1} X_{sell}^{perennialproducts} * p_{pricecoefficient}^{AD} * ep_{market}^{perennialproducts} \\
& - \sum_t X_{hire}^{oxen} * p_{price}^{pairofoxenperday} * CNYID_{wc} - \sum_t X_{hire}^{labor} * p_{wage}^{labor} * CNYID_{wc} \\
& - (1 + r_{interestrate}^{deposit}) * \sum_{cs,t-1} X_{take}^{loan} \geq MCC_t + CTU_{wc}
\end{aligned}$$

MCC_t is minimum cash consumption of the agent at time t .

wp = worst case prices

$CNYID_{wc} = 1$, is consider worst case input demand next year

$CNYBL_{wc} = 1$, is consider worst case prices to buy livestock

$PSLPOCA = 0.5$, is price scaling up factor to sell livestock

$PSLPOCA_{WC} = 2$, is price scaling up factor to buy livestock in worst cases

$CTU_{wc} = 0$, is worst case cash top up

Final static equilibrium cash balances

Shock cash balance at $t=T$

At the final period where there is shock in the previous period the net cash flow should be greater than or equal to the minimum cash requirement of the agent plus a shock

year cash to up.

$$\begin{aligned}
& \sum_{c,s,t} X_{sell}^{shockcrop harvest FSE} * wp_{market}^{crop} * p_{coefficient}^{consumption} + \sum_{l,t} X_{sell}^{livestock} * ep_{market}^{livestock} + \\
& \sum_{l,t} X_{sell}^{livestock FSE} * wp_{market}^{livestock} + \sum_{p,t} X_{maintain}^{perennials} * C_{maintain perennials}^{variable cost} * CNYID_{wc} + \\
& \sum_{p,t} X_{establish}^{perennials} * ep_{price}^{seedling} * SD * CNYID_{wc} + \sum_{h,l,p,t} X_{sell}^{hh labor} * p_{wage}^{off-farm} + \\
& \sum_{cs,s,t} X_{take}^{shock loan} + X_{deposit_t}^{cash} - \sum_{i,t} X_{buy}^{inputs} * ep_{market}^{input price} * CNYID_{wc} - \\
& \sum_{c,s,t} X_{shock buy}^{food} * wp_{market}^{crop} * p_{coefficient}^{consumption} - \sum_{s,t} X_{shock cash consumption}^{forgone} - \\
& \sum_{l,t} X_{buy}^{livestock FSE} * wp_{market}^{bought livestock} * p_{buying}^{top up} * CNYBL_{wc} * PSLPOCA - \\
& \sum_{l,t} X_{keep}^{livestock FSE} * C_{keep livestock}^{variable cost} * CNYID_{wc} - \sum_{l,t} X_{sell}^{shock livestock FSE} * wp_{market}^{livestock} - \\
& \sum_{p,t} X_{sell}^{perennial products} * p_{price coefficient}^{AD} * ep_{market}^{perennial products} - \\
& \sum_t X_{hire}^{oxen} * p_{price}^{pair of oxen per day} * CNYID_{wc} - \\
& \sum_t X_{hire}^{labor} * p_{wage}^{labor} * CNYID_{wc} - (1 + r_{interest rate}^{deposit}) * \sum_{cs,t-1} X_{take}^{loan} \geq MCC_t + CTU_{wc}
\end{aligned}$$

Start of year at transition to FSE $t=T$

$$\begin{aligned}
& \sum_{i,t} X_{buy}^{inputs} * ep_{market}^{input price} + \sum_{c,t} X_{consume}^{bought crops} * ep_{market}^{bought crops} * p_{coefficient}^{consumption} + \\
& \sum_{l,t} X_{buy}^{livestock} * ep_{market}^{bought livestock} * p_{buying}^{top up} \\
& + \sum_{l,t} X_{buy}^{livestock FSE} * ep_{market}^{bought livestock} * p_{buying}^{top up} * PSLPOCA + \\
& \sum_t X_{hire}^{labor} * ep_{wage}^{labor} + \sum_t X_{hire}^{oxen} * ep_{price}^{pair of oxen per day} + \\
& \sum_{t-1} X_{withdraw cash}^{end of previous period} + \sum_{p,t} X_{maintain}^{perennials} * C_{maintain perennials}^{variable cost} +
\end{aligned}$$

$$\begin{aligned}
& \sum_{p,t} X_{establish}^{perennials} * ep_{price}^{seedling} * SD + \sum_{l,t} X_{keep}^{livestockFSE} * C_{keeplivestock}^{variablecost} + X_{deposit_t}^{cash} + \\
& \sum_{cs,t-1} X_{take}^{loan} * (1 + DIF * r_{interestrate}^{loan}) - \sum_{c,t-1} X_{sell}^{cropharvest} * ep_{market}^{cropprice} - \\
& \sum_{l,t-1} X_{sell}^{livestockproducts} * ep_{market}^{livestockproducts} - \\
& \sum_{p,t-1} X_{sell}^{perennialproducts} * p_{pricecoefficient}^{AD} * ep_{market}^{perennialproducts} - \\
& \sum_{h,lp,t} X_{sell}^{hhlabor} * p_{wage}^{off-farm} - \sum_{t-1} X_{cashtransfer}^{startofnextyear} - \sum_{cs,t-1} X_{deposit}^{cash} * (1 + r_{interestrate}^{deposit}) \leq 0
\end{aligned}$$

Final static equilibrium $t=T$

$$\begin{aligned}
& \sum_{i,t} X_{buy}^{inputs} * ep_{market}^{inputprice} + \sum_{c,t} X_{consume}^{boughtcrops} * ep_{market}^{boughtcrops} * p_{coefficient}^{consumption} + \\
& \sum_{l,t} X_{buy}^{livestockFSE} * ep_{market}^{boughtlivestock} * p_{buying}^{topup} * PSLPOCA + \sum_t X_{hire}^{labor} * ep_{wage}^{labor} + \\
& \sum_t X_{hire}^{oxen} * ep_{price}^{pairofoxenperday} + \sum_{t-1} X_{withdrawcash}^{endofpreviousperiod} + \\
& \sum_{p,t} X_{maintain}^{perennials} * C_{maintainperennials}^{variablecost} + \sum_{p,t} X_{establish}^{perennials} * ep_{price}^{seedling} * SD + \\
& \sum_{l,t} X_{keep}^{livestockFSE} * C_{keeplivestock}^{variablecost} + SIF * \sum_{cs,t} X_{shockreservetake}^{loan} * r_{interestrate}^{loan} - \\
& \sum_{c,t} X_{sell}^{cropharvest} * ep_{market}^{cropprice} - \sum_{l,t} X_{sell}^{livestockproducts} * ep_{market}^{livestockproducts} - \\
& \sum_{l,t} X_{sell}^{livestockFSE} * ep_{market}^{livestock} - \sum_{h,lp,t} X_{sell}^{hhlabor} * p_{wage}^{off-farm} - \sum_{cs,t} X_{deposit}^{cash} * r_{interestrate}^{deposit} \leq 0
\end{aligned}$$

Minimum cash consumption

At any time t the total amount of cash withdrawn at the end of the previous period should at least cover household's minimum consumption requirement MCC_t .

$$\sum_{t-1} X_{withdrawcash}^{endofperiod} + X_{forgone}^{cashconsumption} \geq MCC_t$$

Minimum cash consumption FSE

In the last period $t = T$ the total amount of cash withdrawn should at least cover household's minimum consumption requirement at the same period MCC_t .

$$\sum_t X_{withdrawcash}^{endofperiod} + X_{forgone}^{cashconsumption} \geq MCC_t$$

Investment

Perennials

Perennials are defined as assets. Agents have three tree perennials as options for investment. *Perennials* = *AcaciaDecurrense* (*AD*), *Bamboo* (*BAM*), *Eucalyptus* (*EUC*) *Acacia Decurrense* and *bamboo* can only grow in the Dega AEZ while *eucalyptus* can grow anywhere. The lifetime of investment in *AD*, *BAM* and *EUC* is 7, 4 and 9 years respectively. Cutting down is harvesting for perennials. There are different harvest options for each perennial. *Perennialharvestoptions* (*o*) = *logs* (*culms*), *charcoal*, *sellstanding* Charcoal is only applicable for *AD*. Establishing, maintaining and cutting down plantation are integer activities.

Plantation capacity at establishment *age=0* & *t=1*

At $t = 1$ and age ($a = 0$) the total area of plated trees is strictly equal to the area of trees maintained in the same period.

$$\sum_{p, t=1} X_{establish}^{perennial} - \sum_{p, t=1, a=0} X_{maintain}^{perennials} == 0$$

Plantation capacity (*age>0*) & *t=1*

At $t = 1$ and age ($a > 0$) the total area of trees harvested (cut down) and the total area of trees maintained (kept) is strictly equal to the area of land covered by trees in the previous period. Where TPA_{t-1} is total area covered with trees in the previous year

$$\sum_{p, o, t=1, a>0} X_{cutdown}^{perennial} + \sum_{p, t=1, a>0} X_{maintain}^{perennials} == TPA_{t-1}$$

Plantation capacity at establishment (*age=0*) & *t>1*

At $t > 1$ and age ($a = 0$) the total area of plated trees is strictly equal to the area of trees maintained in the same period.

$$\sum_{p, t>1} X_{establish}^{perennial} - \sum_{p, t>1, a=0} X_{maintain}^{perennials} == 0$$

Plantation capacity *age>0* & *t>1*

At $t > 1$ and age ($a > 0$) the total area of trees harvested (cut down) and the total area of trees maintained (kept) is strictly equal to the area of trees maintained (kept)

in the previous period.

$$\sum_{p,o, t,a} X_{cutdown}^{perennial} + \sum_{p,t, a} X_{maintain}^{perennials} == \sum_{p,t-1, a-1} X_{maintain}^{perennials}$$

Forestry product balance

The total amount of perennial products (v) sold at any time t should be less than or equal to the amount harvested at the same period.

$v = \{AD \text{ logs}, AD \text{ leaves}, AD \text{ charcoal}, AD \text{ standing logs}, BAM \text{ culms}, EU \text{ C logs}, EU \text{ C leaves}\}$

$$\sum_{p,v, t} X_{sell}^{perennialproducts} \leq \sum_{p,o, t,a} X_{cutdown}^{perennial}$$

Plantation capacity final static equilibrium

At the final period $t = T$ for all tree ages $a > 0$ the total area of plantation harvested, and total area of perennial land maintained must be equal to total area maintained in the previous age.

$$\sum_{p,o, t=T, a>0} X_{cutdown}^{perennial} + \sum_{p,t=T, a>0} X_{maintain}^{perennials} - \sum_{p,t=T, a-1} X_{maintain}^{perennials} = 0$$

Plantation capacity transition to final static equilibrium

At the final period $t = T$ for all tree ages $a > 0$ the total area of plantation harvested, and total area of perennial land maintained must be equal to total area maintained in the previous age and in the previous period.

$$\sum_{p,o, t=T, a>0} X_{cutdown}^{perennial} + \sum_{p,t=T, a>0} X_{maintain}^{perennials} - \sum_{p,T-1, a-1} X_{maintain}^{perennials} = 0$$

Livestock

Agents invest in livestock. Livestock in the model is introduced as an asset. Livestock production options l for agents are: $l = cow, bull, ram, ewe, doe, buck$ Cow and bull have a lifetime of 9 years while ram, ewe, doe and buck have a lifetime of 6 years.

Inputs

Housing capacity for livestock $t < T$

In all periods except the last period, the total housing requirement of livestock of all ages kept and livestock of less than a year old raised (which will be turned in to calf at

the end of the period) should not be bigger than the general livestock housing limit.

$$\sum_{l,a,t} X_{keep}^{livestock} * HR_{l,a} + \sum_{l,t} X_{raise}^{livestock} * HR_{l,a=1} \leq GLH_l$$

$GLH_l = 10$ unit, general livestock housing limit

$HR_{l,a}$ is housing requirement of livestock by ages

$$HR_{l,a} = \begin{cases} 1 & , \text{cow and bull} \\ 0 & , \text{ram, ewe, doe and buck} \end{cases}$$

Housing capacity for livestock FSE $t=T$

In the last period, the total housing requirement of livestock of all ages kept should not be bigger than the general livestock housing limit.

$$\sum_{l,a,t} X_{keep}^{livestockFSE} * HR_{l,a} + \sum_{l,t} X_{raise}^{livestock} * HR_{l,a=1} \leq GLH_l$$

Feeding balance $t < T$

In all periods except the last period, the total feed requirement of livestock of all ages kept and livestock of less than a year old raised should not be bigger than the feed capacity from communal property and the amount of pasture grown on own plot in the same period.

$$\sum_{l,a,t} X_{keep}^{livestock} * FR_{l,a} + \sum_{l,t} X_{raise}^{livestock} * FR_{l,a=1} - \sum_c X_{grow}^{pasture} \leq FCP_l$$

$FCP_l = 50ha$, is feed capacity from common property (communal grazing)

$FR_{l,a}$ is feed requirement of livestock by ages

Feeding balance FSE $t=T$

In the last period, the total feed requirement of livestock of all ages kept should not be bigger than the feed capacity from communal property and the amount of pasture grown on own plot in the same period.

$$\sum_{l,t} X_{keep}^{livestockFSE} * FR_{l,a} - \sum_{c,t} X_{grow}^{pasture} \leq FCP_l$$

Livestock products

Raw ongoing livestock products = cow milk

Raw final livestock products = beef, mutton

Butter is the only bought and sold livestock product

Agents consume butter, cow milk, cheese, beef and mutton

Processed products = butter, cheese

Milk use balance (for all t)

At any time t in the planning periods the total amount of milk consumed at home and used as an input to process cheese and butter should not be bigger than the total amount of milk collected in the same period.

$$\sum_t X_{consume}^{producedlivestockproducts} + \sum_t X_{consume}^{processedbutterandcheese} * MR_{lp} + \sum_t X_{sell}^{butter} * MR_{lp} - \sum_t X_{collected}^{milk} \leq 0$$

Milk requirement of livestock products (MR_{lp}) per 1 kg of butter and cheese is 16 litters and 10 litters respectively.

Milk product balance $t < T$

For all periods except the last period, the total amount of milk collected is strictly equal to the total milk collecting capacity of the agent.

$$\sum_t X_{collected}^{milk} - \sum_{l,a,t} X_{keep}^{livestock} * Q_{l,a} \leq 0$$

$Q_{l,a}$ is annual quantity of livestock product for each livestock type.

e.g. bull of age 9 gives 300kg of beef

Milk product balance FSE $t = T$

In the last period, the total amount of milk collected is strictly equal to the total milk collecting capacity of the agent.

$$\sum_t X_{collected}^{milk} - \sum_{l,a,t} X_{keep}^{livestockFSE} * Q_{l,a}^{FSE} \leq 0$$

Meat product balance $t < T$

For all periods except the last period, the total amount of beef and mutton collected should not be bigger than the total meat obtained from slaughtered animals at the end of the previous period.

$$\sum_{l,t} X_{consume}^{producedbeefandmutton} - \sum_{l,a,t-1} X_{slaughter}^{endofperiod} * Q_{l,a} \leq 0$$

Meat product balance FSE $t = T$

In the last period, the total amount of beef and mutton collected should not be bigger than the total meat obtained from slaughtered animals at the end of the previous period.

$$\sum_{l,t} X_{consume}^{producedbeefandmutton} - \sum_{l,a,t} X_{slaughter}^{endofperiodFSE} * Q_{l,a}^{FSE} \leq 0$$

Oxen draft power

Pairs of oxen $t > T$

In all periods except the last period, available pairs of oxen should not be bigger than the available bulls who can plough.

$$2 * \sum_{l=bull,t} X_{keep}^{livestock} - \sum_t X_{transfer}^{oxendraftpower} \leq 0$$

Bulls can plough after year 2 to year 9

Ploughing requires 2 oxen

Pairs of oxen $t = T$

In the last period, available pairs of oxen should not be bigger than the available bulls who can plough.

$$2 * \sum_{l=bull,t} X_{keep}^{livestockFSE} - \sum_t X_{transfer}^{oxendraftpower} \leq 0$$

Oxen draft power *for all t*

In all periods the total quantity of oxen draft power demanded to plough should not be bigger than the total amount of hired oxen and oxen draft power from own livestock.

$$\sum_{c,t} X_{grow}^{crops} * L_{dd}^{draftpower} - \sum_{lp,t} X_{hire}^{oxen} - \sum_t X_{transfer}^{oxendraftpower} * LLP * OxH_{day} \leq 0$$

$OxH_{day} = 6$, is oxen hours per day

LLP is length of labor periods

lp is labor periods

Livestock balance

Livestock balance start of period ($t < T$) and $a = 0$

In all periods except the last period, the total heads of new-born livestock kept, raised or sold after birth is strictly equal to the total heads of new borne bought and new offspring obtained in the same period.

$$\sum_{l,a=0,t} X_{keep}^{livestock} + \sum_{l,t} X_{raise}^{livestock} + \sum_{l,t} X_{sell}^{livestockafterbirth} - \sum_{l,a=0,t} X_{buy}^{livestock} - \sum_{l,a=0,t} X_{keep}^{livestock} * Pr_{offspring} = 0$$

$Pr_{offspring}$ is the probability of having an offspring

$$Pr_{offspring} = \begin{cases} 1/offspringcount & , \text{ if livestock type can give offspring} \\ 0 & , \text{ otherwise} \end{cases}$$

Livestock balance start of period ($t=0$) and $a=0$

At the end of the period $t=0$, the total heads of new-born livestock kept, raised or sold after birth is strictly equal to the total heads of livestock of age 1 available in the same period.

$$\sum_{l,a=0,t=0} X_{keep}^{livestock} + \sum_{l,t} X_{raise}^{livestock} + \sum_{l,t} X_{sell}^{livestockafterbirth} - LH_{t=0}^{a=1} = 0$$

$LH_{t=0}^{a=1}$, is the total heads of age 1 livestock available as an initial asset for agents before the beginning of the planning period.

Livestock balance end of period ($0 \leq t \leq T$) and $a = 1$

In all periods including $t=0$ except the last period and for all livestock of age 1, the total heads of 1-year old livestock sold at end of period, slaughtered at end of period,

reserved for bad years and transferred to the next period is strictly equal to the total heads of new-born livestock kept in the same period.

$$\sum_{l,a,t} X_{sell}^{livestockatendofperiod} + \sum_{l,a,t} X_{slaughter}^{endofperiod} + \sum_{l,a,t} X_{reserve}^{livestockforshockcase} + \sum_{l,a,t} X_{transfer}^{livestocktonextperiod} - \sum_{l,a-1,t} X_{keep}^{livestock} = 0$$

Livestock balance start of period ($t < T$) and $a = 1$

In all periods except the last period and for all livestock of age 1, the total heads of 1-year old livestock kept is strictly equal to the total heads of 1-year old livestock transferred from the previous period and the total heads of 1-year old livestock bought in the same period.

$$\sum_{l,a-1,t} X_{keep}^{livestock} - \sum_{l,a,t} X_{transfer}^{livestocktonextperiod} - \sum_{l,a=0,t} X_{buy}^{livestock} = 0$$

Livestock balance end of period ($0 \leq t < T$) and $a > 1$

In all periods including $t=0$ except the last period and for all livestock of age 1, the total heads of 1-year old livestock sold at end of period, slaughtered at end of period, reserved for bad years and transferred to the next period is strictly equal to the total heads of new-born livestock raised in the same period.

$$\sum_{l,a,t} X_{sell}^{livestockatendofperiod} + \sum_{l,a,t} X_{slaughter}^{endofperiod} + \sum_{l,a,t} X_{reserve}^{livestockforshockcase} + \sum_{l,a,t} X_{transfer}^{livestocktonextperiod} - \sum_{l,t} X_{raise}^{livestock} = 0$$

Livestock balance end of period ($t=0$) and $a > 1$

At $t=0$ and for all livestock of age greater than 1, the total heads of livestock sold at end of period, slaughtered at end of period and transferred to the next period is strictly equal to the total heads of livestock of age 2 and above available in the same period.

$$\sum_{l,a,t} X_{sell}^{livestockatendofperiod} + \sum_{l,a,t} X_{slaughter}^{endofperiod} + \sum_{l,a,t} X_{transfer}^{livestocktonextperiod} = LH_{t=0}^{a>1}$$

Livestock balance end of period ($t < T$) and $a > 1$

In all periods except the last period and for all livestock of age greater than 1, the total heads of livestock sold at end of period, slaughtered at end of period, reserved for bad years and transferred to the next period is strictly equal to the total heads of livestock kept in the same period.

$$\sum_{l,a,t} X_{sell}^{livestockatendofperiod} + \sum_{l,a,t} X_{slaughter}^{endofperiod} + \sum_{l,a,t} X_{reserve}^{livestockforshockcase} + \sum_{l,a,t} X_{transfer}^{livestocktonextperiod} - \sum_{l,a-1,t} X_{keep}^{livestock} = 0$$

Livestock balance start of period ($t < T$) and $a > 1$

In all periods except the last period and for all livestock of age 1, the total heads of livestock kept is strictly equal to the total heads livestock transferred from the previous period and the total heads livestock of age 2 and more bought in the same period.

$$\sum_{l,a,t} X_{keep}^{livestock} - \sum_{l,a,t-1} X_{transfer}^{livestocktonextperiod} - \sum_{l,a,t} X_{buy}^{livestock} = 0$$

Livestock balance end of life ($t=0$) and $a = A$

At $t=0$ and for final age of livestock A , the total heads of livestock sold and slaughtered at end of period is strictly equal to the total heads of livestock at their final age available in the same period.

$$\sum_{l,a,t} X_{sell}^{livestockatendofperiod} + \sum_{l,a,t} X_{slaughter}^{endofperiod} = LH_{t=0}^{a=A}$$

Livestock balance end of life ($t < T$) and $a = A$

In all periods except the last period and for final age of livestock A , the total heads of livestock sold and slaughtered at end of period is strictly equal to the total heads of livestock at their final kept in the previous age in the same period.

$$\sum_{l,a,t} X_{sell}^{livestockatendofperiod} + \sum_{l,a,t} X_{slaughter}^{endofperiod} - \sum_{l,a-1,t} X_{keep}^{livestock} = 0$$

Livestock balance in case of shock ($t < T$)

In all periods except the last period and for all ages of livestock, the total heads of livestock sold in bad years should not be bigger than the total heads of livestock reserved for shocks in the same period.

$$Pr_s * \sum_{l,t} X_{sell}^{shocklivestock} - \sum_{l,s,a,t} X_{reserve}^{livestockforshockcase} \leq 0$$

Livestock balance in FSE $t=T$

In the last period and for all final static equilibrium livestock classes, the total heads of livestock sold at end of period, slaughtered at end of period and reserved for bad years should not be bigger than the total heads of livestock kept and bought in the same period.

$$\begin{aligned} \frac{1}{count} * \sum_{l_{fse},t} X_{keep}^{livestockFSE} + \sum_{l_{fse},t} X_{sell}^{livestockatendofperiodFSE} + \sum_{l_{fse},t} X_{slaughter}^{endofperiodFSE} + \\ \sum_{l_{fse},t} X_{reserve}^{livestockforshockcaseFSE} - \sum_{l_{fse},t} X_{keep}^{livestockFSE} - \sum_{l_{fse},t} X_{buy}^{livestockFSE} \leq 0 \end{aligned}$$

l_{fse} , is final static equilibrium livestock classes. $count =$

Livestock balance transition to FSE $t=T$

In the last period and for all final static equilibrium livestock classes, the total heads of livestock sold at end of period, slaughtered at end of period and reserved for bad years should not be bigger than the total heads of livestock transferred to the last period from T-1.

$$\begin{aligned} \frac{1}{count} * \sum_{l_{fse},t} X_{keep}^{livestockFSE} + \sum_{l_{fse},t} X_{sell}^{livestockatendofperiodFSE} + \\ \sum_{l_{fse},t} X_{slaughter}^{endofperiodFSE} + \sum_{l_{fse},t} X_{reserve}^{livestockforshockcaseFSE} - \\ \sum_{l_{fse},a-1,t-1} X_{transfer}^{livestocktonextperiod} \leq 0 \end{aligned}$$

Livestock balance in case of shock FSE $t=T$

In the last period and for all final static equilibrium livestock classes, the total heads of livestock sold in bad years should not be bigger than the total heads of livestock reserved for shocks in the same period.

$$Pr_s * \sum_{l_{fse},t} X_{sell}^{shocklivestockFSE} - \sum_{l_{fse},s,t} X_{reserve}^{livestockforshockcaseFSE} \leq 0$$

Additional constraints

No goats in dega AEZ

Goats can not be raised or kept in dega because of agroecological reasons.

Consumption

Agents eat injera and wot (sauce). Injera is made from cereals mainly teff, finger millet, barley, wheat or sorghum. Agents can mix cereals to make injera. And, wot is made from mixing pulses (beans, peas, chickpeas, lentils), vegetables and tubers (cabbage, carrots, onions), meat (mainly mutton and beef), milk (yogurt, cheese and butter) and spices (chili - *berbere*).

Own production and buying from market are the main sources of food for agents.

Minimum food (nutrient) consumption

At any time t agents' nutrient consumption from bought and produced crops and livestock products should at least meet the minimum nutrient requirements. MND_t is the minimum nutrient demand.

$$\sum_{c,l} X_{consume}^{boughtfood} * N_p^e + \sum_{c,l} X_{consume}^{producedfood} * N_p^e + X_{forgone}^{shockconsumption} * N_p^e \geq MND_t$$

$N_p^e = \text{nutrient content of each food item}$

Minimum food (nutrient) consumption during shocks in ($t > 1$)

In all future periods, where the previous period is a shock period, the minimum amount of nutrients to consume at time t from bought and produced crop and livestock products should at least meet the minimum nutrient requirements.

$$\sum_{c,l,s,t} X_{consume}^{shockbuyfood} * N_p^e + \sum_{l,t} X_{consume}^{producedlivestock} * N_p^e + \sum_{l,t} X_{consume}^{shockproducedcrop} * N_p^e + X_{forgone}^{consumption} * N_p^e \geq MND_t$$

Minimum protein-energy ratio

At any time in the planning period the total amount of protein obtained from consumption of bought and produced crop and livestock products should be greater than the total amount of energy times the protein-energy ratio.

$$\sum_{c,l,f,t} X_{consume}^{boughtfood} * \left(\frac{protein}{energy} * Energy_c - 17 * Protein_c \right) +$$

$$\sum_{c,l,f,t} X_{consume}^{producedfood} * \left(\frac{protein}{energy} * Energy_c - 17 * Protein_c \right) + X_{unmatched}^{\frac{protein}{energy}} \leq 0$$

$$\frac{protein}{energy} = 0.1, proteinenergyratio$$

$$f = energy, protein$$

$Energy_c$ = energy content of crops (MJ/MJ)

$X_{unmatched}^{\frac{protein}{energy}}$ is penalty if minimum requirement is not fulfilled

(17) is a constant to level the units of protein and energy to simplify computation

Shock minimum protein-energy ratio $t > 1$

In all future periods, where the previous period is a shock period, total amount of protein obtained from consumption of bought and produced crop and livestock products should be greater than the total amount of energy times the protein-energy ratio during shocks.

$$\sum_{c,l,f,t} X_{consume}^{shockbuyfood} * \left(\frac{protein}{energy_{shock}} * Energy_c - 17 * Protein_c \right) +$$

$$\sum_{c,l,f,t} X_{consume}^{producedfood} * \left(\frac{protein}{energy_{shock}} * Energy_c - 17 * Protein_c \right) +$$

$$\sum_{c,l,f,t} X_{consume}^{shockproducedcrop} * \left(\frac{protein}{energy_{shock}} * Energy_c - 17 * Protein_c \right) + X_{unmatched}^{\frac{protein}{energy_{shock}}} \leq 0$$

$\frac{protein}{energy_{shock}} = 0.07$, protein energy ratio. The notion here is agent's propensity to consume more energy than protein in time of shock compared to normal years.

$X_{unmatched}^{\frac{protein}{energy_{shock}}}$ is penalty if minimum requirement is not fulfilled

Consumption behavior

Based on observed data and focus group discussions we included rules of predetermined consumption behavior as constraints in the model.

Minimum berbere consumption

Berberere is used as a spice. So, its consumption must be constrained proportional to the amount of cereals (flour for injera) consumed. Rule: Per 100kg of injera flour agents consume the minimum berbere consumption is 3kg. Forgone berbere consumption is a penalty imposed on agents when they cannot fulfill the minimum berbere requirements from all sources, which will make the model infeasible otherwise.

$$0.03 \sum_c X_{consume}^{producedcereals} + 0.03 \sum_c X_{consume}^{boughtcereals} X_{produced}^{berbere} - X_{bought}^{berbere} + X_{forgone}^{berbere} \leq 0$$

Minimum berbere consumption during shocks $t > 1$

In all future periods, where the previous period is a shock period, the minimum berbere consumption must not be lower than 3% of the total cereal consumption.

$$0.03 \sum_{c,t} X_{shockconsume}^{producedcereals} + 0.03 \sum_{c,t} X_{shockconsume}^{boughtcereals} - X_{shockconsume}^{boughtberbere} - X_{shockconsume}^{ownberbere} + X_{shockforgone}^{berbereconsumption} \leq 0$$

Maximum berbere consumption

Similarly, observed consumption behavior dictates to set a maximum berbere consumption for a certain proportion of cereals consumed. Rule: As a result, based on focus group discussions and observed data from farm household surveys we set a maximum berbere consumption for 100ks of cereals consumed by agents is 5kg.

$$-0.05 \sum_c X_{produced}^{cereals} - 0.05 \sum_c X_{bought}^{cereals} + X_{produced}^{berbere} + X_{bought}^{berbere} \leq 0$$

Maximum berbere consumption during shocks $t > 1$

In all future periods, where the previous period is a shock period, berbere consumption must not be bigger than 5% of the total cereal consumption.

$$-0.05 \sum_c X_{shockconsume}^{producedcereals} - 0.05 \sum_c X_{shockconsume}^{boughtcereals} + X_{shockconsume}^{boughtberbere} + X_{shockconsume}^{ownberbere} \leq 0$$

Proportion of consumption from own production

Minimum own cereal consumption in kola

The model represents subsistence farmers where substantial portion of consumption comes from own production. Agents in kola have relatively higher productivity than

those in dega AEZ.

Cereals: teff, maize, wheat, barley. Forgone cereal consumption is a penalty imposed when agents fail to fulfill minimum cereal consumption from all sources.

Rule: 50% of consumption comes from own production for all agents in kola

$$e0.5 \left(\sum_c X_{bought}^{cereals} - \sum_c X_{produced}^{cereals} \right) - X_{forgone}^{cereals} \leq 0 \quad \forall AEZ = kola$$

Minimum own cereal consumption in dega

Attributed to lower productivity compared to kola and high reliance on perennials and livestock, agents in dega are assumed to fulfill a relatively lower amount of their cereal consumption from own production. Moreover, potatoes constitute substantial portion of consumption in dega. Rule: 25% of consumption comes from own production for all agents in dega

$$0.25 \left(\sum_c X_{bought}^{cereals} - \sum_c X_{produced}^{cereals} \right) - X_{forgone}^{cereals} \leq 0 \quad \forall AEZ = dega$$

Minimum potato consumption in dega

Potatoes are only produced in dega AEZ. And, it constitutes substantial portion of their consumption. Forgone potato consumption is a penalty when they cannot fulfill their demand from all sources.

Rule: minimum potato consumption in dega is 25%

$$0.25 \sum_{c,t} X_{produced}^{cereals} + 0.25 \sum_{c,t} X_{bought}^{cereals} - X_{produced}^{potatoes} - X_{bought}^{potatoes} + X_{forgone}^{potatoconsumption} \leq 0$$

$$\forall AEZ = dega$$

Minimum potato consumption in dega during shocks $t > 1$

In all future periods, where the previous period is a shock period, minimum potato consumption in dega AEZ is 25% of total food items consumed.

Rule: minimum potato consumption in dega is 25%

$$0.25 \sum_{c,s,t} X_{shockconsume}^{producedcereals} + 0.25 \sum_{c,t} X_{shockconsume}^{boughtcereals} - X_{shockconsume}^{producedpotato} - X_{shockconsume}^{boughtpotato} + X_{shockforgone}^{potatoconsumption} \leq 0 \quad \forall AEZ = dega$$

Maximum potato consumption in dega

Agents can not only eat potatoes even if it is available abundantly.

Rule: maximum potato consumption should not be greater than 50%

$$-0.5 \sum_{c,t} X_{produced}^{cereals} - 0.5 \sum_{c,t} X_{bought}^{cereals} + X_{produced}^{potatoes} + X_{bought}^{potatoes} \leq 0 \quad \forall AEZ = dega$$

Maximum potato consumption in dega during shocks $t > 1$

In all future periods, where the previous period is a shock period, maximum potato consumption should not be greater than 50% of total bought and produced food consumption in dega AEZ

$$\begin{aligned} & -0.5 \sum_{c,s,t} X_{shockconsume}^{producedcereals} - 0.5 \sum_{c,s,t} X_{shockconsume}^{boughtcereals} + \\ & X_{shockconsume}^{producedcereals} + X_{shockconsume}^{boughtcereals} \leq 0 \quad \forall AEZ = dega \end{aligned}$$

Maximum meat consumption

Rule: The maximum meat consumption per 100kg of cereals consumed is 20kg

$Meat = beef, mutton$

Meat can only be produced in the farm for consumption (no bought meat)

$$-0.2 \sum_c X_{produced}^{cereals} - 0.2 \sum_c X_{bought}^{cereals} + X_{produced}^{meat} + X_{bought}^{meat} \leq 0$$

Appendix B

Data sources for the farm decision model

The farm decision model used data from different sources to initialize the model. Both primary and secondary source of data are used to parameterize the model. The following table shows the model to data (requirement and source) connections of the different features in the farm decision model.

Table 7.1: Model to data connections of the farm decision model

Model features	Model sub-features	Data requirements	Data sources	Corresponding equations (in Appendix A)
Crop production	land balance	farm size	own survey (2018)	land balances eq. pp. 104
	croprotation	rotation limit	FGDs (2018)	croprotation eq. pp. 105
	labor balance	household (agent) demographic data	own survey (2018)	labor balance eqns. pp.105-106
	input balance	input demand (eg fertilizers, improved seeds)	own survey (2018)	input balance eq. pp. 106
	food storage balance	storable crops, storage life time	own survey (2018), FGDs (2018)	storage balance equs. pp. 106 – 108
Investment	perennials	types and initial endowments of tree perennials	own survey (2018)	perennial eqn. pp. 119
		life time, plantation capacity, harvest options, variable cost including labor and output prices	own survey (2018)	perennial eqn. pp. 119,120
	livestock	livestock types kept by age	own survey (2018), CSA data 2019	livestock eqn. pp. 120

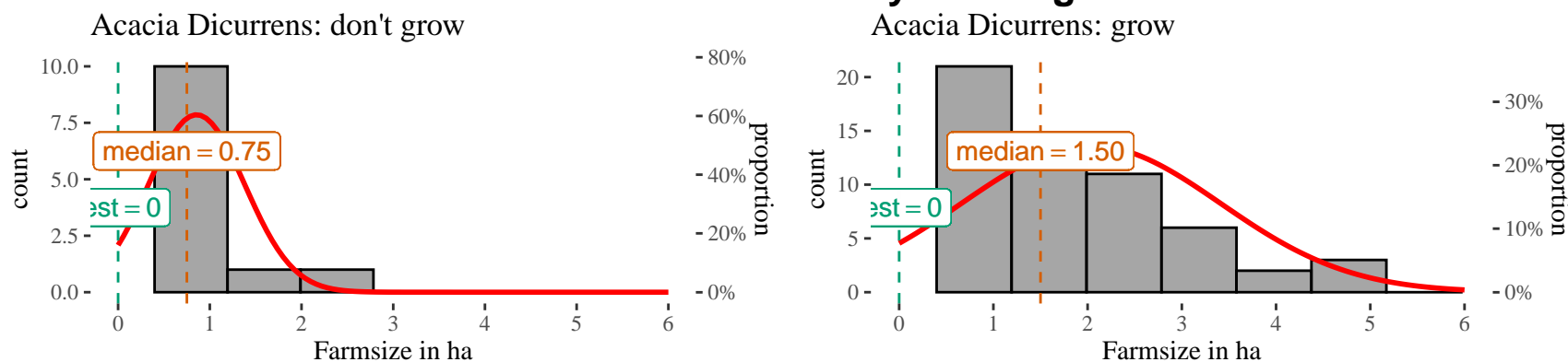
		inputs: livestock housing limit, feed requirements, grazing land feed capacity, livestock products, marketability of products, oxen draft power	own survey (2018), CSA data 2019	livestock eqns. pp. 121-127
consumption	minimum food (nutrient) consumption	nutrient contents of all food items in the model (mainly energy and protein), minimum energy to protein ratio	FAO (food and nutrition technical report series 1) and USDA online database	consumption eqns. pp. 128-129
	predetermined consumption behaviour	minimum and maximum consumption limits for berbere (chilli) and shiro (beans), proportions of consumption from own production (for cereals, potatoes and meat)	own survey (2018), FGDs (2018)	consumption eqns. pp. 130-132
Others	credit and savings	credit sources, credit limit, interest rate, deposit rate	own survey (2018), KIIs (2018), Amhara Credit and Saving Institute ACSI annual report 2019	credit and savings eqns. pp. 112-113
	Ex-ante planning	expected loss of crop diseases, worst case prices and rates, probability of shocks,	own survey (2018), feedback from the econometric analysis	shock equations throughout appendix A
	exogenous variables	Prices, yields, discount rate, inflation rate	own survey (2018), CSA data 2019	

Appendix C

Distribution of endowments by crop/tree growers

Acacia Dicurrens

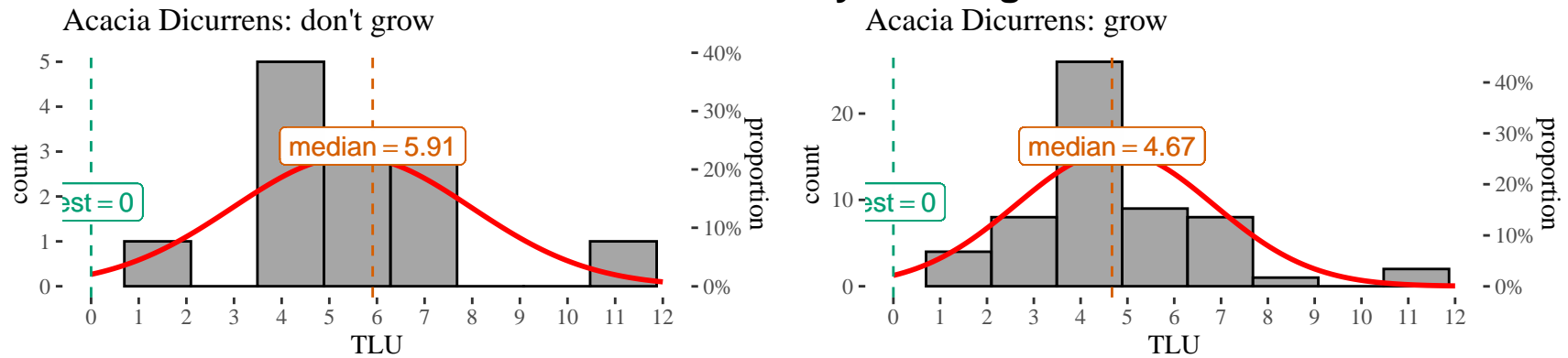
Distribution of farm size by acacia grower



Data source: own survey

Figure 7.1: Distribution of farm size by acacia grower

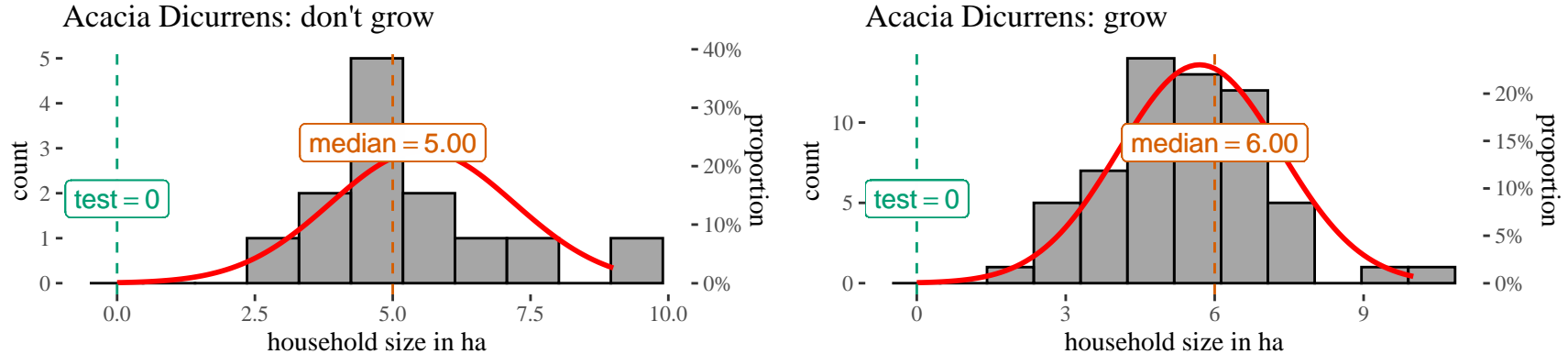
Distribution of TLU by acacia grower



Data source: own survey

Figure 7.2: Distribution of TLU by acacia grower

Distribution of household size by acacia grower



Data source: own survey

Figure 7.3: Distribution of household size by acacia grower

Barley

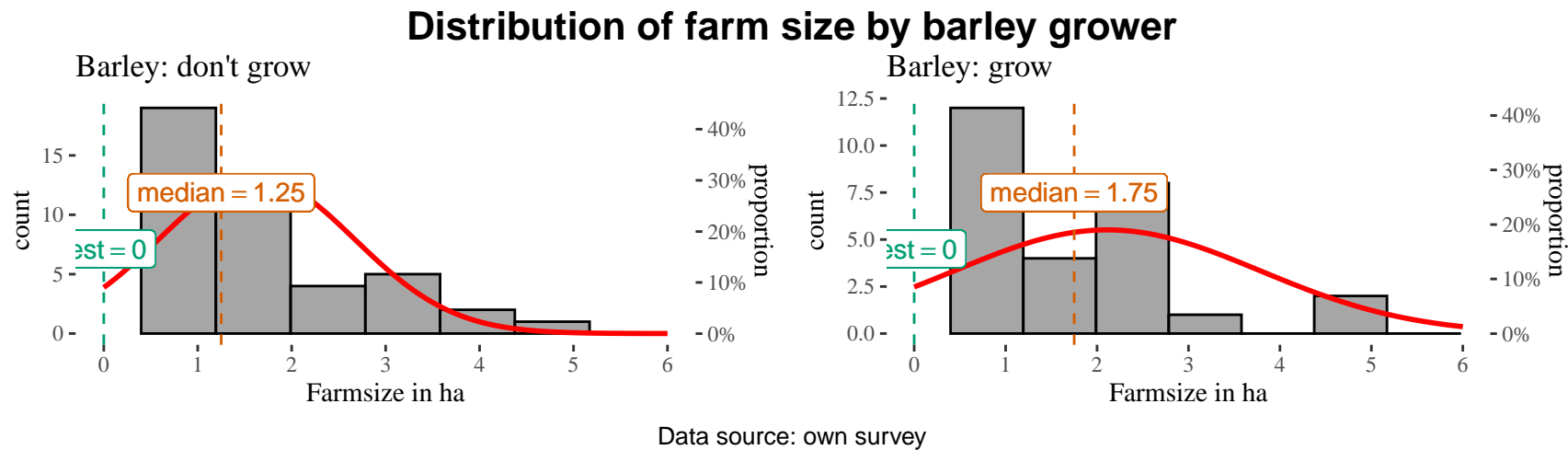


Figure 7.4: Distribution of farm size by barley grower

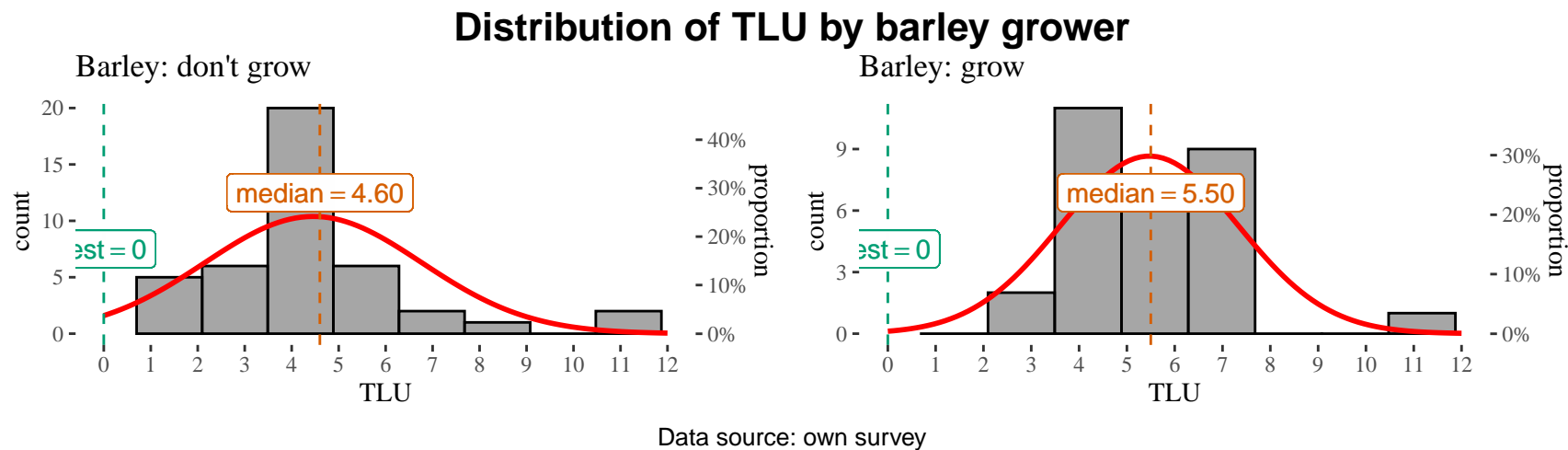


Figure 7.5: Distribution of TLU by barley grower

Distribution of household size by barley grower

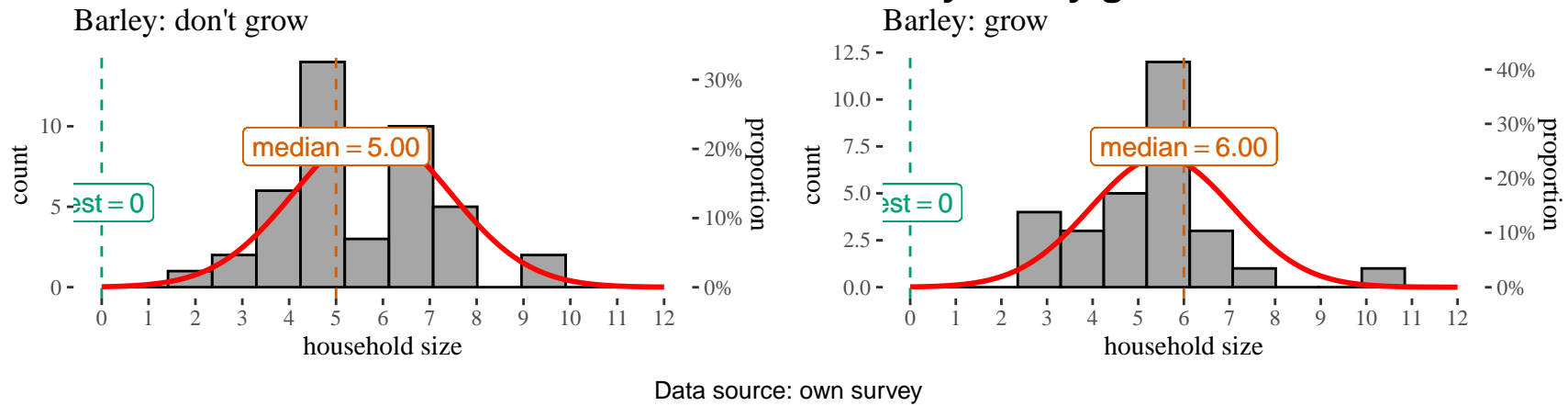


Figure 7.6: Distribution of household size by barley grower

Potatoes

Distribution of farm size by potato grower

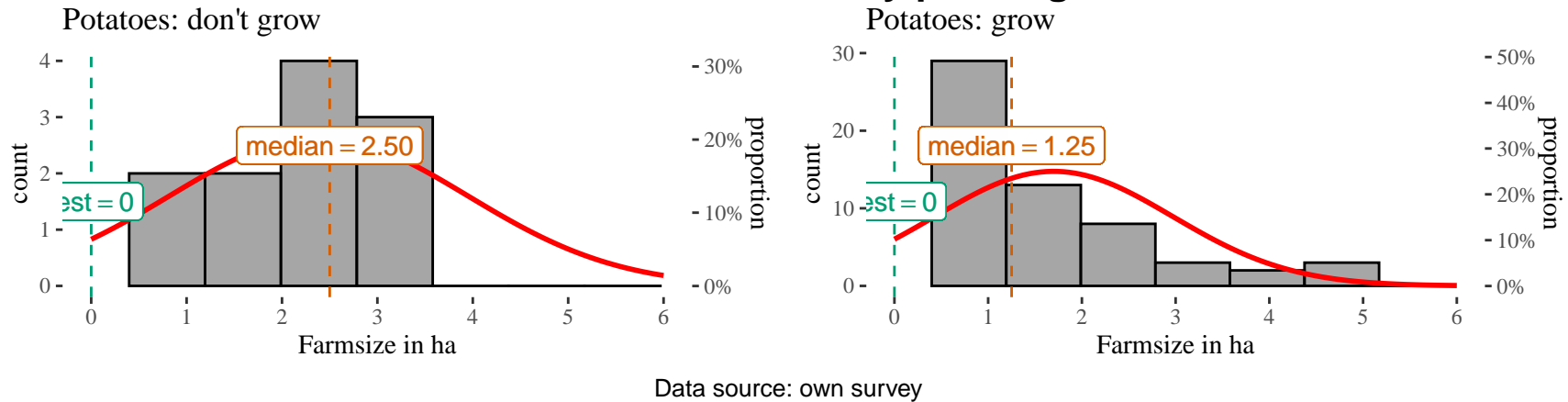
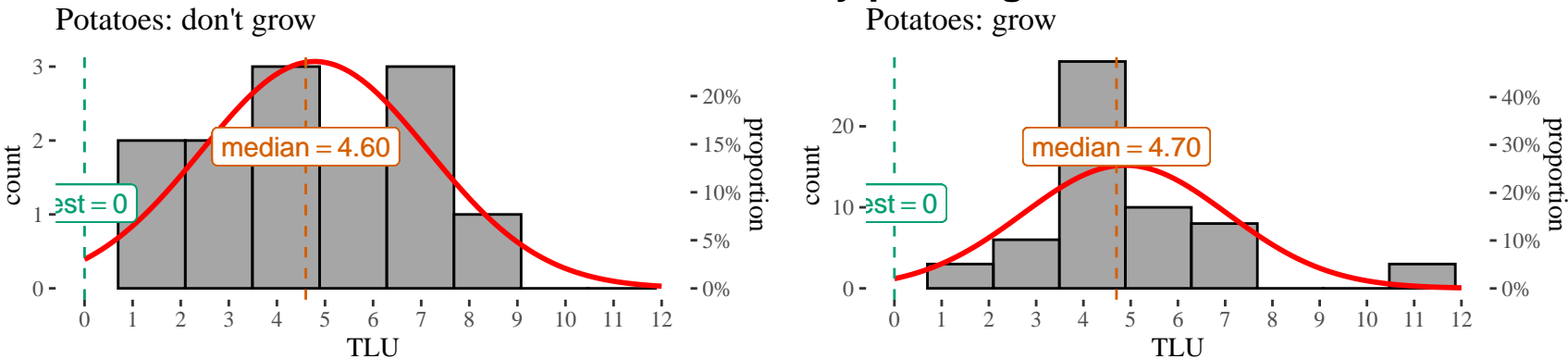


Figure 7.7: Distribution of farm size by potato grower

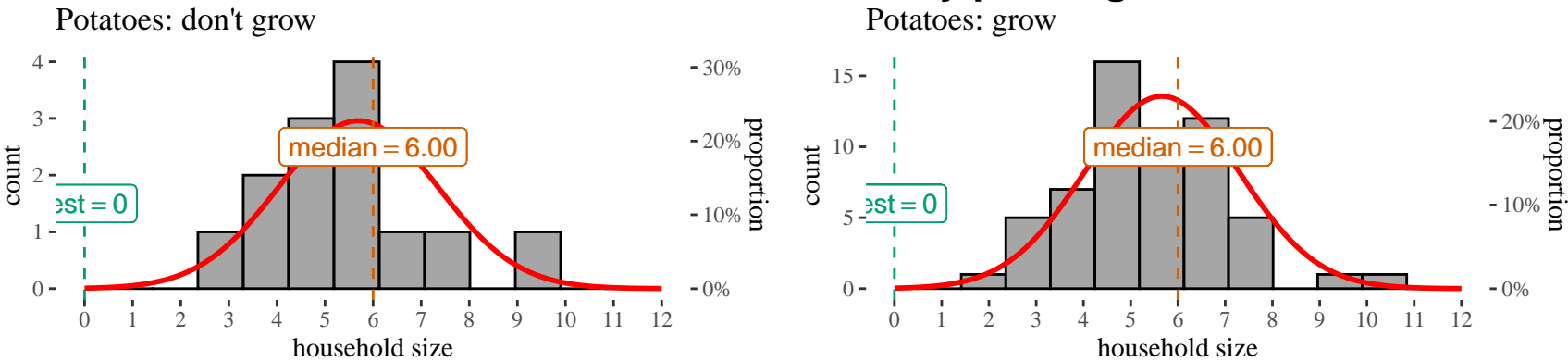
Distribution of TLU by potato grower



Data source: own survey

Figure 7.8: Distribution of TLU by potato grower

Distribution of household size by potato grower

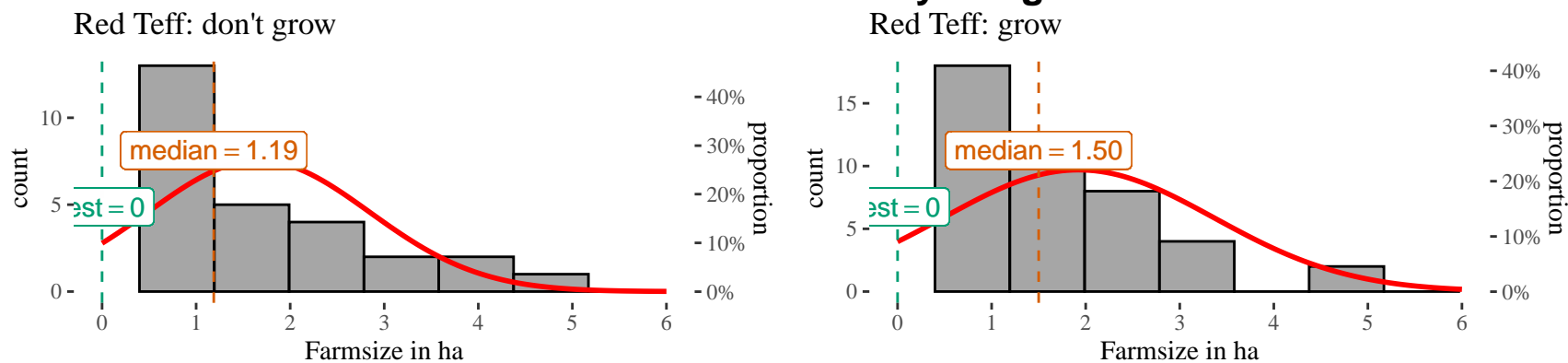


Data source: own survey

Figure 7.9: Distribution of household size by potato grower

Red Teff

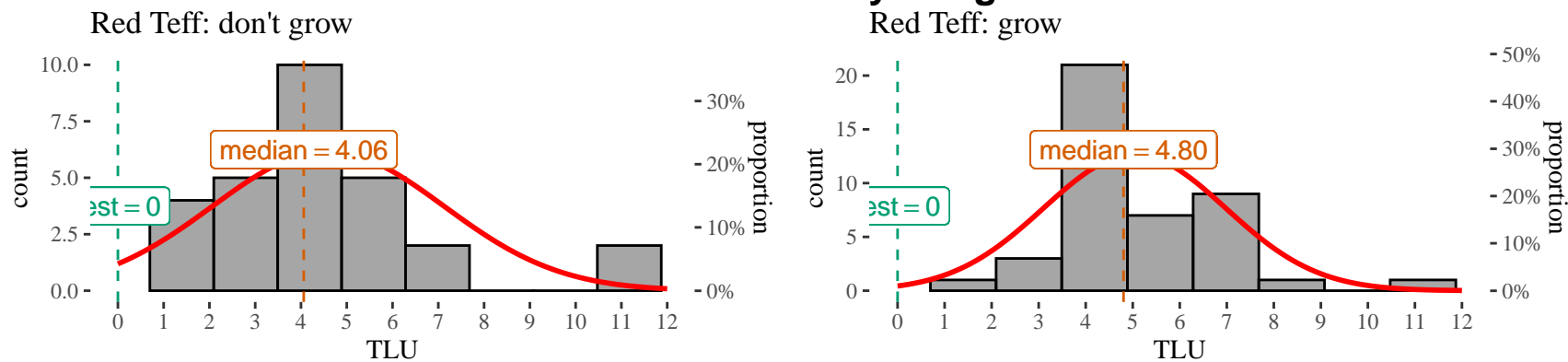
Distribution of farm size by teff grower



Data source: own survey

Figure 7.10: Distribution of farm size by teff grower

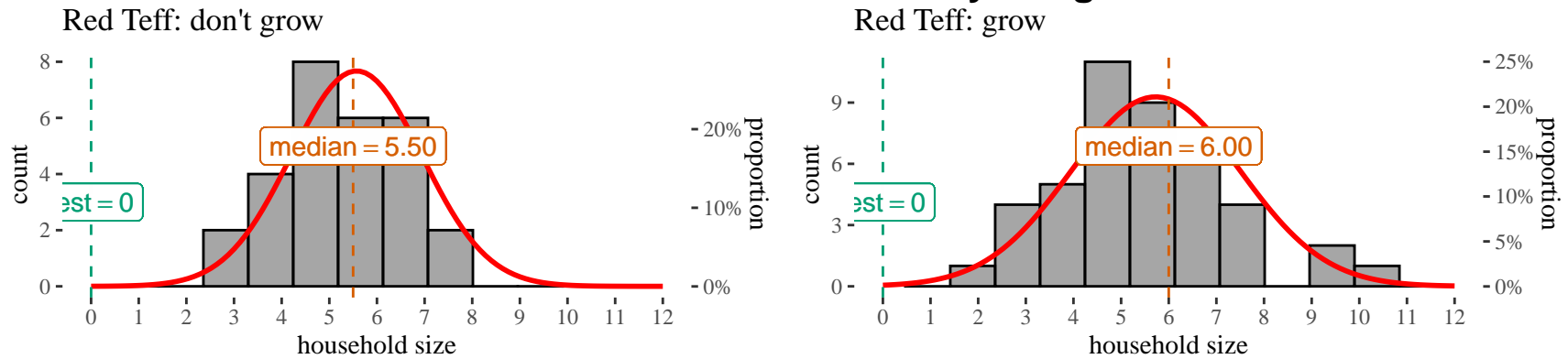
Distribution of TLU by teff grower



Data source: own survey

Figure 7.11: Distribution of TLU by teff grower

Distribution of household size by teff grower

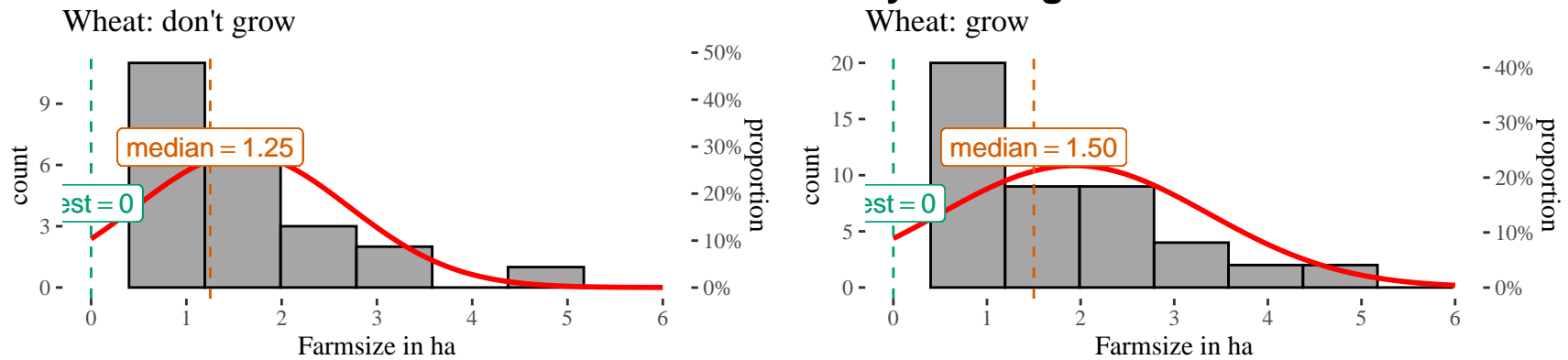


Data source: own survey

Figure 7.12: Distribution of household size by teff grower

Wheat

Distribution of farm size by wheat grower



Data source: own survey

Figure 7.13: Distribution of farm size by wheat grower

Distribution of TLU by wheat grower

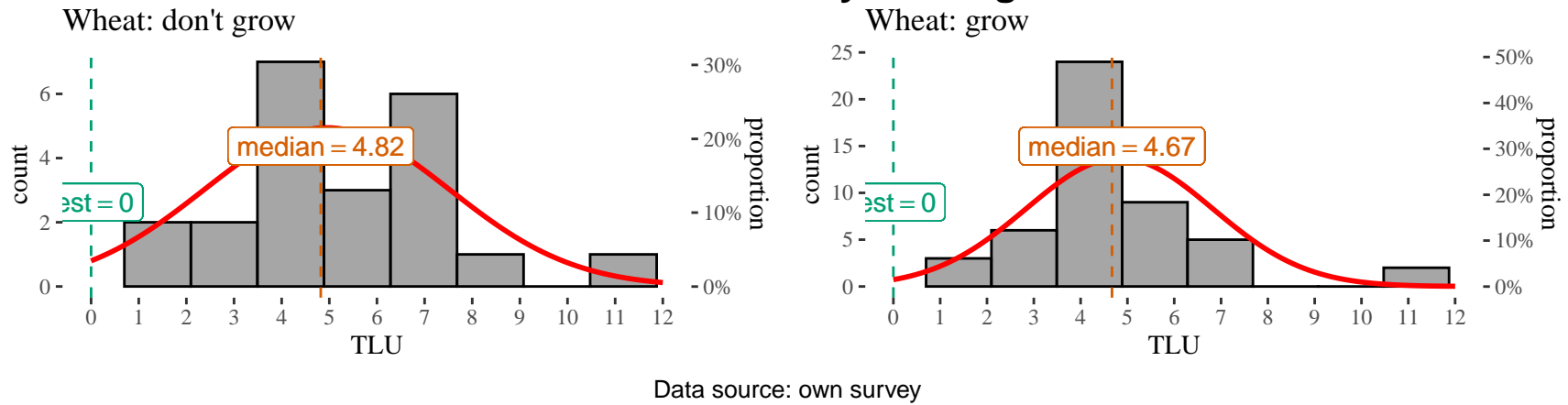


Figure 7.14: Distribution of TLU by wheat grower

Distribution of household size by wheat grower

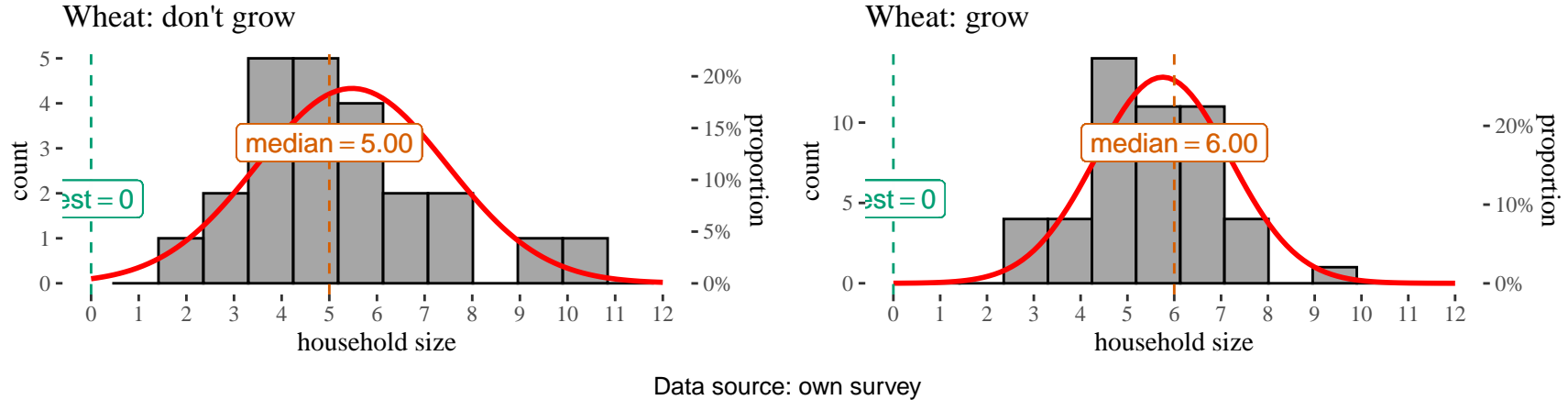


Figure 7.15: Distribution of household size by wheat grower

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