# MANAGING VULNERABILITY TO RISKS IN SMALLHOLDER FARMING: ESSAYS ON CLIMATE CHANGE ADAPTATION AND SUSTAINABLE AGRICULTURAL INTENSIFICATION IN DEVELOPING COUNTRIES

Chalmers Kyalo Mulwa

Submitted in partial fulfillment of the

requirements for the degree of

Doctor of Philosophy

in the School of Economics

UNIVERSITY of CAPE TOWN

## Declaration

I, CHALMERS KYALO MULWA , hereby declare that the work on which this thesis is based is my original work (except where acknowledgements indicate otherwise) and that neither the whole work nor any part of it has been, is being, or is to be submitted for another degree in this or any other university. I authorise the University to reproduce for the purpose of research either the whole or any portion of the contents in any manner whatsoever.

Signature: Signed by candidate Date: 24.07.2020

July 2020

Supervised by: Professor Martine Visser

## Abstract

The recent threat of climate change has exacerbated the inherent risks in smallholder farming such as soil degradation, resulting in an unprecedented decline in agricultural yields in developing countries. This has threatened the livelihoods of large segments of populations that are heavily dependent on agriculture for survival in these regions. This dissertation focuses on identifying barriers and enablers of effective management of these risks, with an aim of coming up with potential policy interventions that can reduce vulnerability to the mentioned risks. To achieve this, the dissertation utilizes various methods and approaches as well as diverse datasets in two countries in sub Saharan Africa i.e. Namibia and Kenya.

Diversification into non-farm activities is seen by many as a risk management strategy in rural areas where highly variable low farm incomes are transformed into stable high non-farm incomes, thus improving the welfare of the rural populations. While this theory of change is uncontested, the importance that the agricultural sector plays as a source of livelihood for rural populations, as well as food provisioning for urban populations, cannot be downplayed. This is more so given the limited non-farm opportunities in developing countries and the exponential population growth in these countries. The two factors combined impede on the envisioned transformation of rural production sectors and also create a sub-population of food insecure urban poor due to rural-urban migration. To mitigate these problems, rural agricultural development is still paramount and strategies that enhance resilience to risks in the sector are still vital. Chapter 2 of this dissertation focuses on this issue and addresses how farm diversification can be leveraged for improved food security in the rural areas, which has potential spill-over effects to other segments of the population. Focussing on northern Namibia, the study evaluates how different levels of diversification in both crop and livestock farming affect household food security outcomes i.e. per capita food expenditure and dietary diversity score. The study employs relatively new econometric methods in these type of studies to evaluate the joint determinants to both crop and livestock diversification, as well as their singular and joint effect on mentioned food security outcomes. The results show that high levels of diversification in either enterprise leads to high food security outcomes.

Combined with climate change adaptation strategies that create resilience of agricultural production to climatic shocks, the use of sustainable agricultural intensification practices can further enhance productivity in the sector. Inputs like inorganic fertilizer, organic manure and improved seeds can further build on resilient systems to improve yields. Chapter 3 of this dissertation addresses this issue by looking at whether changes in the larger agri-food systems can

be used to incentivize take up of such practices at the farm level. The study evaluates how the emergence of large traders in smallholder grain markets can drive the uptake of inorganic and organic fertilizer and improved seeds. The study thus expands the intervention space available to policy makers who have in the past resorted to potentially distortionary direct policies in the input markets e.g. through subsidy provision, as well as in the output markets e.g. through regulation of prices. To achieve this, the study uses a large panel dataset from Kenya spanning over a decade to evaluate how engagements between farmers and these market actors can be leveraged to drive adoption of these sustainable intensification inputs. Results show that engagements between large grain traders and farmers enhance use of inorganic fertilizer. There is no evidence that these engagements lead to enhanced use of improved seeds or manure. However, past use of improved seeds and manure are shown to affect their subsequent use, implying path dependency in the use of these sustainable inputs hence low dis-adoption rates.

Traditional tecnnology adoption stidues show that access to information is a critical success factor for the uptake of new technology. Proxy variables for information access, for example proximity to extension services or frequency of extension contact, have consistently been shown to be positively correlated with technology adoption. In the context of climate change, access to weather information can be a critical factor to adoption of adaptation technology. Chapter 4 of this dissertation deals with this issue and assesses whether provision of weather information to farmers can enhance adoption of improved farming technologies that are resilient to climatic shocks. The study focuses on northern Namibia where access to such information, as the study shows, is very limited. A framed experiment approach is utilised to evaluate how climate change-induced uncertainty affects farmers' decision making in a farming season, based on their elicited behavioural attitudes towards risk and uncertainty. Further, the study tests whether providing weather information that reduces this uncertainty leads to adoption of technologies that are welfare improving. Lastly, the demand for weather information is assessed by eliciting the willingness to pay for information under various levels of weather uncertainty. Results indicate that high levels of uncertainty dampen uptake of welfare improving technologies, regardless of individual attitudes towards uncertainty. Availing of weather information leads to welfare improving technology choice, given the prevailing levels of weather uncertainty. There is also a high demand for weather information which is shown to increase with increase in the level of weather uncertainty.

The chapters in the dissertation therefore identify key policy variables that can be used to manage vulnerability to risks emanating from climate change and unsustainable production in smallholder farming. Access to comprehensive climate information encompassing weather information and climate change-specific management information on both crop and livestock farming is shown to be a key factor in the uptake of adaptation strategies like use of resilient inputs and farm diversification. Interventions along the value chain like teaming up with large market actors in a private-public engagement is shown to be a potential pathway towards enhancing uptake of sustainable intensification inputs. Other policy variables like credit provision, high education and access to off-farm incomes are also key in explaining uptake of risk management strategies by smallholder farmers in Namibia and Kenya.

## Acknowledgements

Utmost thanks go to my family, my wife and kids, for their love, support and sacrifice during this PhD journey. They made a long and testing journey seem easy by actively and passively encouraging me to push on. I am also highly indebted to my parents, especially my mother, who saw the value of education and struggled to keep a son in school against all odds. This PhD is a culmination of their sacrifice. Special thanks also to extended family members for supporting me and my family the entire duration of my PhD journey. Aunt Puline Kavinya and uncle Aggrey Mutinda are of special mention in this regard.

My profound gratitude to my supervisor and mentor, Martine, whose leadership and guidance has made the success of this PhD possible. Martine has been more than a PhD supervisor, offering her support and emphathy in so many ways. Her deep knowledge of issues tackeld in this thesis and experience have shaped this thesis to what it is. The lessons and skills I have learnt from her are life-long, and I cannot say thank you enough. One could never wish for a better supervisor.

I would also like to thank co-authors in one of this thesis essays, Thomas and Milu, for their guidance and support including availing data for analysis. Their input is greatly appreciated. Special thanks also to Menale for the support he has accorded me from earlier days of applying for this PhD opportunity and his comments for improving the essays in this thesis. His input is also greatly appreciated.

The School of Economics  provided a excellent research environment and I benefitted a lot from opportunities to present my work at the school seminars and get feedback. Special thanks to the Environmetal Policy Research Unit (EPRU) for the support and especially the administrator, Felicity, who was always ready to assist.

I would also like to thank fellow doctoral students Abel, George, Kevin, Zachary and Rebecca for the comradeship and the many stimulating discussions we have had that made the PhD journey exciting and less drudgery.

This PhD was funded by the Swedish International Development Agency (SIDA) through the Environment for Development (EfD) Initiative and administered by the Environmental Policy Research Unit (EPRU) at the University of Cape Town’s (UCT) School of Economics. Partial funding to conduct field studies was also obtained from the African Climate and Development Initiative (ACDI)  through the Adaptation at Scale in Semi-Arid Regions (ASSAR) project. Data from the Tegemeo Insitute of Agricultural Policy and Development is also used in one of the essays.

To my dearly loved sons, Ethan Mulwa and Jaden Kaboro

**Table of Contents**

**List of Figures**

## List of Tables

# Chapter 1

# 1 Introduction

## 1.1 Overview

Many livelihoods in developing countries are directly depended on the natural resource base, the most important being agricultural production. Without investments to boost resilience of agricultural production against adverse changes, these livelihoods remain exposed and vulnerable. This is more so because most of the agricultural production in developing countries is characterized by smallholder, rain-fed cultivation with little use of intensification inputs (inorganic fertilizer and improved seeds) and mechanization. Such production systems are very vulnerable to adverse changes to the climate and changes to soil quality, such as the continued soil degradation in developing countries and the recent phenomena of climate change. Adaptation to stressors like climatic shocks and soil degrading factors create resilience in production systems such that these systems are able to resist shock disturbances or recover to their original state of productivity after shock (Gil et al. 2017).

For the most part, literature and policy on agricultural development in developing countries has centred on enhancing the uptake of improved technologies at the smallholder household level for higher yields. Adverse changes in the natural environment (soil and climate) are necessitating a rethink to this approach. Population pressures experienced in sub-Saharan Africa, for example, has meant that the same plots of land are cultivated season after season leading to soil nutrient depletion, soil infertility and a stagnation in yields (Drechsel, Dagmar, and de Vries 2001). Low use of soil fertility enhancing inputs further contribute to nutrient mining. Evidence also shows that at a certain level of soil infertility, the soil loses its ability to absorb nutrients from inorganic fertilizers, further enhancing demand-side factors for non-use of the input given the low profitability (Marenya and Barrett 2009).

The recent global change phenomena is by far proving to be the biggest adverse change in the natural environment to threaten agricultural production and consequently many livelihoods dependent on agriculture. The impacts of climate change are worsening the low input use - soil infertility problem that has pervasively contributed to sub-optimal productivity frontiers, through major climate stressors like droughts, floods and seasonal weather fluctuations like dry spells and early/late cessation of rains. The IPCC (2012) projects a marked increase in the intensity of droughts and incidences of low precipitation in the sub-Saharan Africa (SSA) region, leading to a projected decline of up to 25%-30% in crop yields by the year 2030 (UNEP 2015).

Regarding soil degradation, while some degree of this phenomena is driven by nature, the problem is largely exacerbated by human practices (Karlen and Rice 2015). Unsustainable land use practices like continuously cultivating the same piece of land with no fallow periods, low use of organic and inorganic fertilizer, minimal uptake of soil amendment practices, all lead to mining of important soil minerals rendering soils infertile (Kamau et al., 2014; Tittonell et al., 2008; Liu et al., 2006). In addition, low productivity given low soil fertility may led to opening up more forest cover to create additional land for cultivation, further degrading soils through exposure to surface run offs and wind erosion.

Diminished agricultural productivity from climate change impacts and soil degradation leads to food shortages and rising food prices which affect both the rural and urban poor, entrenching food insecurity and poverty in large segments of the developing world's population (Leichenko and Silva 2014; Muller et al. 2011; Ahmed, Diffenbaugh, and Hertel 2009; Hertel, Burke, and Lobell 2010). The coping strategies undertaken by households in the aftermath of climatic shocks such as sale of assets and withdrawing kids from school, further entrench household poverty traps (Carter et al., 2007; van den Berg, 2010). With more than 52% of all fertile, food producing soils globally now being classified as degraded, soil degradation needs to be recognised as one of the most pressing problems facing humanity alongside climate change and the two should be addressed simultaneously (Young, Orsini, and Fitzpatrick 2015). Soil degradation is defined as the decline in any or all of the characteristics which make soil suitable for producing food (Young, Orsini, and Fitzpatrick 2015). Thus degraded soils are incapable of supporting agriculture even in times of good climatic conditions.

Evidence shows that adoption of simple sustainable agricultural intensification practices (SAIPs) can lead to restoration of soil fertility and an increase in crop yields (Kassie et al. 2008; Kihara et al. 2016; Marenya and Barrett 2007). These practices include *inter alia*; conservation agricultural practices like minimum/zero tillage, crop rotations and intercropping, retention of crop residues and cover crops; soil and water conservation practices (SWCs); application of organic manure; and use of intensification inputs like inorganic fertilizers and improved seed. With soil management practices raising soil fertility through restoration of soil organic matter (SOM) and soil carbon, the soil is ready to absorb nutrients from intensification inputs like inorganic fertilizer, therefore raising yields. Improved seeds also function well under the fertile soils.

Incidentally, most of the above mentioned sustainable intensification practices are part of a collection of climate change adaptation practices encompassed in a broader term referred to as climate smart agriculture (CSA). Use of SAIPs like SWC are part of the practices used to mitigate crop losses during dry spells as a consequence of the changing climate. Crop intercropping, a key sustainable intensification practice used to manage soil fertility as well as moisture preservation (for example maize-legume and banana-coffee intercrop regimes), has been shown to be an effective CSA mechanism in controlling pests and diseases whose increased incidence is attributed to rising temperatures (Campbell et al. 2014). Also, conservation agriculture through use of zero/minimum tillage and herbicides to control weeds is an important SAIP practice which prevents soil compacting leading to soil degradation. The practice is also an important CSA strategy for soil moisture conservation in instances of dry spells.

Perhaps the most important linkage between climate change adaptation and sustainable agricultural intensification in the context of this thesis, other than the mentioned soil fertility management, is that of use of improved seeds and farm diversification. While improved seeds use is a standard intensification practice used since the advent of the green revolution, the meaning of the term is now changing as environmental risks intensify. Improved seeds for a long time has referred to hybrid seeds i.e. seeds that do extremely well in situations where the weather is good, but perform poorly generally in situations of low rainfall. They are also non-recyclable and farmers are advised to plant them only once for optimal yields. In the context of risk management given the changing climate, improved seeds are now being bred to withstand climate stressors and for sustainability. Thus "improved seeds" as a sustainable agricultural intensification practice is now a conventional climate change adaptation strategy where the term may refer to seeds that are drought tolerant, water tolerant or early maturing to mitigate against early stop of rains.

On the other hand, incorporating livestock farming with crop farming to exploit synergies in the two farm enterprises, is a key sustainable intensification practice; animals provide manure for the improvement of soil fertility and traction power for ploughing farming areas, while crops provide fodder for the livestock. Incidentally, this is an important climate change adaptation practice where diversification in farming enterprises create resilience to climatic shocks, as well as providing households with a diversified nutritional base.

Broadly, the interdependence between climate change and land (soil) degradation is uncontested; land degradation allows the escape of carbon dioxide trapped in soils to the atmosphere, accumulation of which contributes to global warming. The UNCCD (2007), for instance, estimates that achieving land degradation neutrality (LDN) by restoring and rehabilitating 12 million hectares of degraded land per year could help close carbon dioxide gas emissions gap by up to 25% in the year 2030. On the other hand, another interdependence closer to one of the subjects of this thesis regards soil degradation and carbon. Soil carbon has been shown to be essential in helping plants absorb nutrients with evidence showing that degraded soils low on carbon have a diminished ability to take up nutrients, including those in applied inorganic fertilizers like nitrogen (Kihara et al., 2016; Marenya and Barrett, 2009; Zingore, 2011).

Consequently, practices that limit the escape of soil carbon to the atmosphere as carbon dioxide yield double dividends i.e. that of helping soils remain fertile, while at the same time mitigating global warming. At the same time, practices that help produce more food intensively prevent the opening up of more land to feed growing populations, a practice shown to contribute to global warming through release of carbon to the atmosphere. This underscores the broad complementarity between climate change adaptation and sustainable agricultural intensification. Indeed, Climate Smart Agriculture (CSA) provides the foundations for incentivizing and enabling sustainable agricultural intensification through its emphasis on risk management, information flows and local institutions to support adaptive capacity (Campbell et al. 2014).

## 1.2 Thesis contribution

The interlinkages between climate change adaptation and sustainable agricultural intensification motivate the focus of this thesis. Despite the myriad of challenges facing smallholder agricultural production in SSA, uptake of technology that intensifies production sustainably and creates resilience in production is still quite low. This is not unique to climate change adaptation and sustainable intensification though, as the paradox of low adoption of agricultural technologies and interventions has preoccupied most development economics literature in the past. Barriers to technology uptake identified in the literature span across institutional factors like missing credit markets; socio-economic barriers like liquidity constraints; physical infrastructure like poor road networks; behavioural barriers like risk/uncertainty aversion; and poor/inadequate policy response. However, the literature is still nascent on the adoption of technology that addresses the emerging threats of climate change and soil degradation, as well as action areas where intervention could lead to adequate management of risks posed by these threats to livelihoods. Essays in this dissertation add to this growing literature by assessing the barriers and enablers to climate change adaptation and sustainable agricultural intensification in smallholder farms.

In the climate change adaptation literature, climate information has been cited as a key success factor towards enhancing adaptation (Singh et al. 2017; Di Falco, Veronesi, and Yesuf 2011; Mulwa et al., 2017). Farmers with limited access to precise weather forecasts may not be able to adequately prepare for adverse weather in a season. Information on the available appropriate responses to specific projected climate outcomes may also be key to enabling adaptation. This hypothesis is tested in the first essay of the thesis. The role played by provision of weather information in enhancing take up of farming technology is assessed using a framed experiment approach where farmers choose farming technologies with and without information on weather outcomes within the season and the difference in the payoffs of these choices are compared.

The foregoing discussion show farm diversification as an important sustainable agricultural practice and climate change adaptation strategy. Diversification in farm enterprises and labour has been shown to be an effective way of adapting to climate change. Extant literature explores various aspects of diversification including livestock, crop and off-farm diversification (Megersa et al., 2014; Tibesigwa, Visser and Turpie, 2015; Barrett et al., 2017; Asfaw, Pallante and Palma, 2018). The second essay in this thesis looks at whether farm diversification can be leveraged for food security in semi-arid areas like northern Namibia. The essay focuses on both crop and livestock diversification in a household, which is a novel approach unexplored in existing literature. Given the precarious nature of livelihoods in semi-arid areas like northern Namibia and the ongoing government efforts to combat climate change, the essay’s policy implications are topical.

As the section on overview above shows, soil degradation is a serious issue in SSA and soil management practices are critical for the improvement of soil fertility and productivity. The third essay in this thesis interrogates this issue and explores to what extent the marketing value chain, specifically large grain traders involvement in smallholder grain markets, can be leveraged to drive uptake of soil amendment practices at the farm level. This is a novel approach with the potential of unlocking other policy intervention avenues for the enhancement of technology uptake in smallholder farming households. Sustainable agricultural practices explored in the essay are inorganic and organic fertilizer, and improved seed use.

To achieve all this, the essays utilize relatively new econometric methodologies in these type of studies, for example, the dynamic probit model, the two stage residual inclusion (2SRI) method and the panel data double hurdle model. Both panel data and cross-sectional datasets are used as well as experimental data collected using a framed experiment. The essays also cover regions where few such studies have been carried out i.e. northern Namibia.

### 1.3 Thesis Objectives

The broad objectives forming essays within the thesis are enumerated below, with sub-objectives explored within each broad objective also shown;

1. ***To evaluate the effect of farm diversification on food security among smallholder farmers in northern Namibia***

1.1 Assess the joint determinants to crop and livestock diversification

1.2 Evaluate the effect of crop, livestock and overall diversification on food security outcomes

1.3 Evaluate how different levels of combined diversification in crop and livestock enterprises affect food security outcomes

2. ***To assess the role of large grain traders in incentivizing the adoption of sustainable agricultural intensification practices in Kenya***

2.1 Assess the determinants to large grain sales among farming households

2.2 Assess the determinants to adoption of fertilizer, improved seeds and manure

2.3 Evaluate the dynamic effect in the adoption of SAIPS

3. ***To assess how provision of weather information affects choice of farming technology in a farming season in northern Namibia***

3.1 Assess the role of weather uncertainty in dampening technology uptake

3.2 Assess the demand for weather information under different levels of weather uncertainty

3.3 Evaluate the welfare effects of providing weather information under various levels of weather uncertainty

### 1.4 Choice of study areas

Two of the chapters in this study are from data collected in northern Namibia while the third is from longitudinal data from Kenya. Semi-arid areas in developing countries have been predicted to be affected the most in terms of agricultural losses due to climate change. The UNDP (2015) puts Namibia as the seventh most at-risk country in terms of climate change related agricultural losses. Given the fragile livelihoods therein, urgent measures are imminent to raise the adaptive capacity of the people and production systems in such countries. To support policy, studies on barriers and success factors for climate change adaptation are crucial for such regions, and so is documenting evidence of the impact of such measures on people's welfare.

Further, there is a dearth of empirical studies on rural household livelihoods and welfare from Namibia. The low literature citation for studies from the country in this dissertation points to that fact. This is despite planned adaptation programs happening in the country through government plans on climate change for example the National Climate Policy for Namibia-2011 (GRN 2011). Studies in this dissertation can result in policy recommendations relevant for the country, which was a big motivation for the choice of Namibia as a study country, focusing on climate change adaptation. The northern part of the country was chosen because it is the largely populated region and also where smallholder farming, both crop and livestock, is the main source of livelihood. Data from a study carried out in the region under the Adaptation at Scale in Semi-Arid Regions (ASSAR) project has been used in the first and second essays of this thesis.

In Kenya, rising rural population and scarcity of land has led to declining land productivity due to soil degradation (Muyanga, Jayne, and Burke 2013). Farmers are farming increasingly small portions of land with some areas like the Central and Kisii highlands leading in unsustainably intensely cultivated lands. Given the low input use in the region, continuous soil mining without replenishment has in some cases resulted to severe soil degradation contributing to low productivity. Some studies have attributed the low demand for fertilizer to low yield-response of crops to fertilizer use, since the soils are so depleted of organic matter that their capacity to take up nitrogen is very low (Kihara et al. 2016; Marenya and Barrett 2009). The region is in dire need of sustainable intensification for soil fertility restoration and rural poverty alleviation. This motivates the choice of the country to study the dimension of SAIP adoption on soil fertility management.

In addition, one of the hypothesis being tested in the thesis is whether large grain traders can be used to incentivize the adoption of SAIPs at the farm level. While such market actors have been unobserved in rural grain markets, recent evidence show the emergence of these in Kenya and Zambia (Sitko et al. 2017). Kenya's unique advantage for choice as a study area on this aspect lies in the presence of a large panel dataset on rural livelihoods spanning over a decade. The study has been carried out through a long-term collaboration between Egerton University's Tegemeo institute, an agricultural policy think tank in Kenya, and Michigan State University's department of Agricultural, Food, and Resource Economics in the United States. The data from this project called TAMPA (Tegemeo Agricultural Monitoring and Policy Analysis) has been utilized for the third essay in this thesis.

### References

Ahmed, S. A., Diffenbaugh, N. S., & Hertel, T. W. (2009). Climate volatility deepens poverty vulnerability in developing countries. *Environmental Research Letters*, *4*(3). https://doi.org/10.1088/1748-9326/4/3/034004

Campbell, B. M., Thornton, P., Zougmoré, R., van Asten, P., & Lipper, L. (2014). Sustainable intensification: What is its role in climate smart agriculture? *Current Opinion in Environmental Sustainability*, *8*, 39–43. https://doi.org/10.1016/j.cosust.2014.07.002

Carter, M. R., Little, P. D., Mogues, T., & Negatu, W. (2007). Poverty Traps and Natural Disasters in Ethiopia and Honduras. *World Development*, *35*(5), 835–856. https://doi.org/10.1016/j.worlddev.2006.09.010

Drechsel, P., Dagmar, K., & de Vries, F. P. (2001). Soil Nutrient Depletion and Population Growth in Sub-Saharan Africa : A Malthusian Nexus? *Population and Environment*, *22*(4), 411–423.

Gil, J. D. B., Cohn, A. S., Duncan, J., & Newton, P. (2017). The resilience of integrated agricultural systems to climate change. *Wiley Interdisciplinary Reviews: Climate Change*, *8:e461*. https://doi.org/10.1002/wcc.461

Government of the Repulic of Namibia. (2011). *NATIONAL CLIMATE POLICY FOR NAMIBIA-2011*.

Hertel, T. W., Burke, M. B., & Lobell, D. B. (2010). The poverty implications of climate-induced crop yield changes by 2030. *Global Environmental Change*, *20*(4), 577–585. https://doi.org/10.1016/j.gloenvcha.2010.07.001

IPCC. (2012). Managing the risks of extreme events and disasters to advance climate change adaptation. In *Ipcc*. https://doi.org/10.1596/978-0-8213-8845-7

Kamau, M., Smale, M., & Mutua, M. (2014). Farmer demand for soil fertility management practices in Kenya's grain basket. *Food Security*, *6*(6), 793–806. https://doi.org/10.1007/s12571-014-0398-5

Karlen, D. L., & Rice, C. W. (2015). Soil degradation: Will humankind ever learn? *Sustainability (Switzerland)*, *7*(9), 12490–12501. https://doi.org/10.3390/su70912490

Kassie, M., Pender, J., Yesuf, M., Kohlin, G., Bluffstone, R., & Mulugeta, E. (2008). Estimating returns to soil conservation adoption in the northern Ethiopian highlands. *Agricultural Economics*, *38*(2), 213–232. https://doi.org/10.1111/j.1574-0862.2007.00295.x

Kihara, J., Nziguheba, G., Zingore, S., Coulibaly, A., Esilaba, A., Kabambe, V., … Huising, J. (2016). Understanding variability in crop response to fertilizer and amendments in sub-Saharan Africa. *Agriculture, Ecosystems and Environment*, *229*, 1–12. https://doi.org/10.1016/j.agee.2016.05.012

Leichenko, R., & Silva, J. A. (2014). Climate change and poverty: Vulnerability, impacts, and alleviation strategies. *Wiley Interdisciplinary Reviews: Climate Change*, *5*(4), 539–556. https://doi.org/10.1002/wcc.287

Marenya, P. P., & Barrett, C. B. (2007). Household-level determinants of adoption of improved natural resources management practices among smallholder farmers in western Kenya. *Food Policy*, *32*(4), 515–536. https://doi.org/10.1016/j.foodpol.2006.10.002

Marenya, P. P., & Barrett, C. B. (2009a). Soil quality and fertilizer use rates among smallholder farmers in western Kenya. *Agricultural Economics*, *40*, 561–572. https://doi.org/10.1111/j.1574-0862.2009.00398.x

Marenya, P. P., & Barrett, C. B. (2009b). State-conditional fertilizer yield response on Western Kenyan Farms. *American Journal of Agricultural Economics*, *91*(4), 991–1006. https://doi.org/10.1111/j.1467-8276.2009.01313.x

Muller, C., Cramer, W., Hare, W. L., & Lotze-Campen, H. (2011). Climate change risks for African agriculture. *Proceedings of the National Academy of Sciences*, *108*(11), 4313–4315. https://doi.org/10.1073/pnas.1015078108

Muyanga, M., Jayne, T. S., & Burke, W. J. (2013). Pathways into and out of Poverty: A Study of Rural Household Wealth Dynamics in Kenya. *Journal of Development Studies*, *49*(10), 1358–1374. https://doi.org/10.1080/00220388.2013.812197

S. Zingore. (2011). Maize roductivity and response to fertilizer use as affected by soil fertility variability, manure application, and cropping system. *Better Crops*, *95*(1).

Sitko, N. J., Jayne, T. S., Burke, W. J., & Muyanga, M. (2017). Food System transformation and Market Evolutions: an analysis of the rise of large-scale grain trading in Sub-Saharan Africa. In *International Development Working Paper (forthcoming). Michigan State University*. https://doi.org/10.13140/RG.2.2.18589.10725

Tittonell, P., Shepherd, K. D., Vanlauwe, B., & Giller, K. E. (2008). Unravelling the effects of soil and crop management on maize productivity in smallholder agricultural systems of western Kenya-An application of classification and regression tree analysis. *Agriculture, Ecosystems and Environment*, *123*(1–3), 137–150. https://doi.org/10.1016/j.agee.2007.05.005

UNCCD. (2007). *Climate change and desertification*. (1). https://doi.org/10.1127/0340-269X/2007/0037-0495

UNEP. (2015). *Africa ' s Adaptation Gap: Climate-change impacts, adaptation challenges and costs for Africa*.

van den Berg, M. (2010). Household income strategies and natural disasters: Dynamic livelihoods in rural Nicaragua. *Ecological Economics*, *69*(3), 592–602. https://doi.org/10.1016/j.ecolecon.2009.09.006

X.Liu, S.J. Herbert, A.M. Hashemi, X. Zhang, G. D. (2006). Effects of agricultural management on soil organic matter and carbon transformation - a review. *Plant Soil and Environment*, *52*(12), 531–543.

Young, R., Orsini, S., & Fitzpatrick, I. (2015). Soil degradation : a major threat to humanity. *Sustainable Food Trust*, 13. Retrieved from http://sustainablefoodtrust.org

# Chapter 2

## 2 Farm diversification and climate change: Implications for Food Security in Northern Namibia


**Abstract**

Limited non-farm opportunities in the rural areas of the developing world, coupled with population growth, means agriculture will continue to play a dominant role as a source of livelihood in these areas. Thus, while rural transformation has dominated recent literature as a way of improving welfare through diversifying into non-farm sectors, improving productivity and resilience to shocks in smallholder agricultural production cannot be downplayed. This is especially so given the changing climatic conditions affecting agricultural production, and thus threatening many livelihoods in rural areas. Farm diversification is an important strategy for creating resilience against climatic shocks in farm production. Using cross-sectional data from northern Namibia, the study assesses the barriers and success factors related to effective crop and livestock enterprises diversification and the effect of these on food security outcomes. A Seemingly Unrelated Regression model is used to assess the joint factors explaining total farm diversification, while a step-wise error correction model is used to evaluate the conditional effect of diversification in each of the two farm enterprises on two measures of food security: food expenditure and dietary diversity. We find that past exposure to climate shocks informs current diversification levels and that access to climate information is a key success factor for both livestock and crop diversification. In terms of food security, greater diversification in either crop or livestock production leads to higher food security outcomes, with neither crop nor livestock diversification showing dominance in affecting food security outcomes. However, an overall higher level of diversification in both livestock and crop enterprises is dominant in explaining food security outcomes.


### 2.1 Introduction

Risk is inherent in small-scale rain-fed agricultural production. Farmers have to contend with seasonal weather uncertainties, the threat of pests and diseases, and post-harvest losses, among other risks. These risks are being exacerbated by the effects of a changing climate; for example, the severity and distribution of important livestock and crop diseases is changing, while incidents of droughts and floods are on the rise (Elad and Pertot, 2014; Thornton et al., 2009; Wetherald and

Manabe, 2002). These effects of climate change are expected to increase poverty incidences in most developing countries and create new poverty pockets in countries with increasing inequality (IPCC, 2014).

Agricultural production has been stagnant in Sub-Saharan Africa (SSA), and there is consensus that the current trend in productivity cannot guarantee food security in the region (Kyalo Willy et al., 2019; Onyutha, 2018). Climatic shocks that further adversely affect food production are a serious threat to food security and livelihoods in the region. While there are adaptation options that can create resilience in agricultural productivity, studies continue to show low adoption rates across the region (Bradshaw et al., 2004; Di Falco et al., 2011; Mulwa et al., 2017; Singh et al., 2017; Smit and Wandel, 2006). In crop farming, such adaptation measures include using seeds adapted to climate-stressors (for example drought resistant seeds) and spreading risks across different crop types (Howden et al. 2007). In livestock farming, farmers can also choose to adopt livestock breeds that are tolerant to climate-stressors, as well as diversify into different livestock types/species (Rojas-Downing et al., 2017).

Recent literature on diversification focuses on rural transformations from predominantly agriculture-related sectors to rural non-farm sectors (see for example Barrett et al., 2017). While this is important in reducing the prevalent disguised unemployment in peasant agriculture, such non-farm opportunities remain largely non-existent in rural areas of SSA. With the recent phenomena of climate change effects threatening to depress agricultural productivity further and jeopardize livelihoods for many in these regions, evaluating strategies for creating resilience in the sector cannot be overlooked (Bradshaw et al., 2004). This study aims to evaluate households' farm diversification as an adaptation strategy to climatic shocks, and the on effect food security.

Most studies assessing farm diversification focus on either crop or livestock diversification (Adjimoti and Kwadzo, 2018; Makate et al., 2016; Mango et al., 2018; Megersa et al., 2014; Rojas-Downing et al., 2017; Tittonell, 2014). Others extending to both farm and non-farm diversification treat farm diversification as one activity that encompasses crop and livestock farming (Berhanu et al., 2007; Martin and Lorenzen, 2016). An exception is Tibesigwa et al. (2015) that compared outcomes of farmers who are specialized in either of the enterprises with those of farmers who practice mixed farming. Considering livestock and crop diversification separately may underestimate joint effect on food security, and does not allow for the identification of barriers to each diversification type. Similarly, comparing specialized systems with mixed ones hides information on how the extent of diversification in each enterprise affects welfare. Furthermore, it is difficult to encounter specialized systems among smallholder farmers, who more often practice a mix of crop and livestock activities (as exemplified in northern Namibia).

Our study adds to this literature by assessing the joint determinants of diversification in both livestock and crop farming, and how the extent of diversification in each activity contributes to food security. Further, in a novel attempt to assess which enterprise diversification contributes most to food security, the study compares food security outcomes for households with varying levels of crop and livestock diversification.

## 2.2 Climate change and farm diversification

Diversification literature identifies factors that "push" farmers to diversify as a hedge against risks, and factors that "pull" farmers to diversify in order to take advantage of other opportunities. In farm diversification, an example of a push factor may be the increasing climate shocks that make it risky to rely on a certain crop (e.g. maize) or livestock type (e.g. cattle) as the only enterprise, necessitating the adoption of a mix of crop and livestock types that may be more resilient to climate shocks. A "pull" factor on the other hand may be the advantage of planting crop mixes that are symbiotic, e.g., planting runner beans that use maize stalks as support, while fixing nitrogen fertilizer for the maize crop.

Climate change affects livestock production through impacts on pasture and water, as well as through diseases associated with climate shocks (Rojas-Downing et al., 2017). Choosing the optimal count of livestock and livestock types to keep is key to mitigating these impacts. Declining pastures and water availability may call for substitution of resource-demanding species like cattle for the more resilient small ruminants like goats and sheep (Gautam and Andersen, 2016). In Namibia, the importance of mixing small ruminants with cattle rearing is more pronounced; while cattle ownership is a symbol of prestige and the animals are used for festivities like weddings, funerals and bride price (Musemwa et al. 2008), the small ruminants are important for providing nutrients and dietary diversity, either through direct consumption or sale. In Ethiopia, Megersa et al., (2014) found that households that were more diversified in livestock production had higher average off-take in livestock sales, had fewer months of food insecurity, and scored higher on household food dietary diversity.

Crop diversification involves the use of different seed varieties of the same crop type, as well as planting of different crop types in a farming season. Agricultural intensification inputs like hybrid seeds have been the core of agricultural transformation since the green revolution. Within the context of a changing climate, improved seeds have to be not just output enhancing but also resilient to shocks like droughts and pests (Lin 2011; Mulwa et al., 2017). Incorporating these types of seeds in a mix of crops and varieties planted can be an important adaptation strategy for resilience. Other benefits of diversified cropping systems include improving soil fertility and expanding household's dietary diversity for improved nutrition uptake.

Studies show that at the subsistence level, diversification into both crop and livestock production is complementary (Berhanu et al., 2007; Megersa et al., 2014). Farmers can use crop residues as livestock feed while animals provide draught power and manure (Megersa et al. 2014). This relationship may however have a threshold level above which competition for scarce resources leads to one crowding out the other. For example, with scarce labor, households may only practice crop farming, which has a higher marginal return to labour, while those with higher labour supply may be able to diversify into livestock (Berhanu, Colman, and Fayissa 2007).

The success factors for diversification as identified in the literature include social capital, asset ownership, government/NGO transfer programs, remittances and off-farm opportunities (Barrett et al., 2001; Davis et al., 2010; Wuepper et al., 2018). Investigating the importance of each of these for diversification in the study region is important for policy. The dearth of literature on agricultural production and food security in the study region further shows the importance of this study.

## 2.3 Study Area

This study was conducted in three regions in northern Namibia: Omusati, Oshana and Oshakati. Climate in the region is semi-arid and rainfall is seasonal and highly variable both in quantity and timing. A changing climate has resulted in shorter rain seasons characterised by high temperatures, late onset of rains and higher incidences of droughts (Repulic of Namibia, 2011). This has exacerbated vulnerability of livelihoods in the region which are highly dependent on natural resources and comprise mostly rain-fed subsistence agriculture. There is low adaptive capacity in the region and Namibia is considered to be among the highly vulnerable African countries with regard to climate change (Reid et al., 2007).

Land use in the region is characterised by combining livestock herding and small-scale cereal production, supplemented by timber and non-timber resources like wild fruits and *mopane* worms (Newsham and Thomas, 2009). A significant proportion of households (25%) participate in off-farm income ventures, while 23% participate in government transfer programs. This number is relatively small, though, compared to those who rely on farming and forest products (timber and non-timber) for livelihoods (see Figure 1).

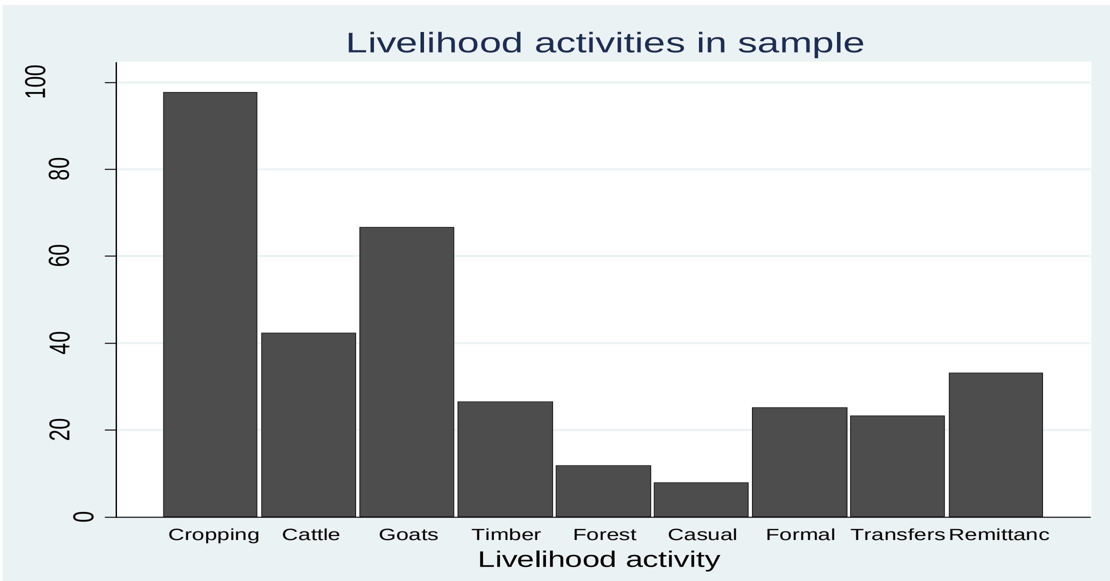


*Figure 2-1: Livelihood activities practiced*

Crop cultivation remains the most practiced livelihood activity in the region while a high proportion also rear livestock (cattle and small ruminants).

## 2.4 Sampling and data

Data for this study come from the Adaptation at Scale in Semi-Arid Regions (ASSAR) project. A multistage random sampling procedure was used to select 650 households from three regions in northern Namibia. First, the three regions (Oshana, Omusati and Oshikoto) were purposively selected based on agricultural productivity and exposure to climate change.

Table 2-1 Descriptive statistics

| Variable | Variable description | Mean | Std. Dev. |
|---|---|---|---|
| *Dependent variables* | | | |
| Improved seed | Household has adopted drought tolerant/early maturing millet varieties (1=yes; 0=no) | 0.18 | - |
| Crop diversification | Herfindahl–Hirschman index (HHI) for crop diversification | 0.58 | 0.24 |
| Livestock diversification | Herfindahl–Hirschman index (HHI) for livestock diversification | 0.63 | 0.24 |
| Food expenditure | Per capita food expenditure (N$) | 112.5 | 141.9 |
| Dietary diversity | Household Dietary diversity score | 6.92 | 1.98 |
| *Explanatory variables* | | | |
| Climate shocks-crop | Past exposure to climate shocks with severe effect on cropping (1=yes; 0=no) | 0.48 | - |
| Climate shocks-livestock | Past exposure to climate shocks with severe effect on livestock (1=yes; 0=no) | 0.35 | - |
| Age | Age of household head | 61.57 | 17.03 |
| Education | Education of household head (years of schooling) | 5.66 | 4.05 |
| Gender | Gender of household head (1=male; 0=female) | 0.43 | - |
| Household size | Total household size (number) | 5.63 | 3.06 |
| Asset index | Assets owned (pca[1] factors) | 1.62e-08 | 1.00 |
| Social capital | Factors of relatives and friends one can go to for help in and outside village if in need | -2.03e-09 | 0.67 |
| Information access-crop | If household received climate information specific to crop management (1=yes; 0=no) | 0.52 | - |
| Information access-livestock | If household received climate information specific to livestock management (1=yes; 0=no) | 0.45 | - |
| Credit access | If household received crop/livestock input credit (1=yes; 0=no) | 0.20 | - |
| Formal employment | If household had access to formal employment opportunities (1=yes; 0=no) | 0.25 | - |
| Government transfers | If household received safety nets from the government (1=yes; 0=no) | 0.23 | - |
| Remittances | If household had access to remittance income (1=yes; 0=no) | 0.33 | - |
| *Location characteristics* | | | |
| Omusati (ref. region) | Omusati region (1=yes; 0=no) | 43.93 | - |
| Oshana | Oshana region (1=yes; 0=no) | 29.19 | - |
| Oshikoto | Oshikoto region (1=yes; 0=no) | 26.88 | - |

Two constituencies were each selected from Oshana and Oshikoto and three from Omusati to capture the diversity within the regions. Random proportionate to size sampling was then used to select villages and households to include in the survey. Data was collected by a team of trained enumerators using as structured questionnaire in the months of August and September 2017.

## 2.5 Construction and description of variables

### 2.5.1 Farm enterprise diversification indices

Different types of indices have been used in the literature to measure livelihood diversification (Davis et al., 2010; Lay et al., Mahmoud, and M'Mukaria, 2008; Wuepper et al., 2018). Our study aimed to investigate not only the number of farming activities a household is engaged in, but also the intensity of engagement in each. To this end, we chose the Herfindahl–Hirschman index (hereafter HHI) which is mostly used in finance to measure market concentration, and has been applied previously in studies similar to ours (see Chen et al., 2018; Wuepper et al., 2018).

Information on crops and seed types grown by a household and area allocated to each was used to construct the crop diversification index, while the livestock diversification index was constructed using information on livestock types and numbers kept by a household. Following Rhoades (1993), we calculate the HH indices as;

$$HHI_{kj} = \sum_{i=1}^{n} (ES_i)^2$$

where *HHI* is the index for household *k* for *j* diversification (crop/livestock), *ES* is the enterprise share (i.e. area share for crop *i or Tropical Livestock Units (TLU)* share for livestock type *i)* and *n* is the number of crops cultivated/livestock types kept per household.

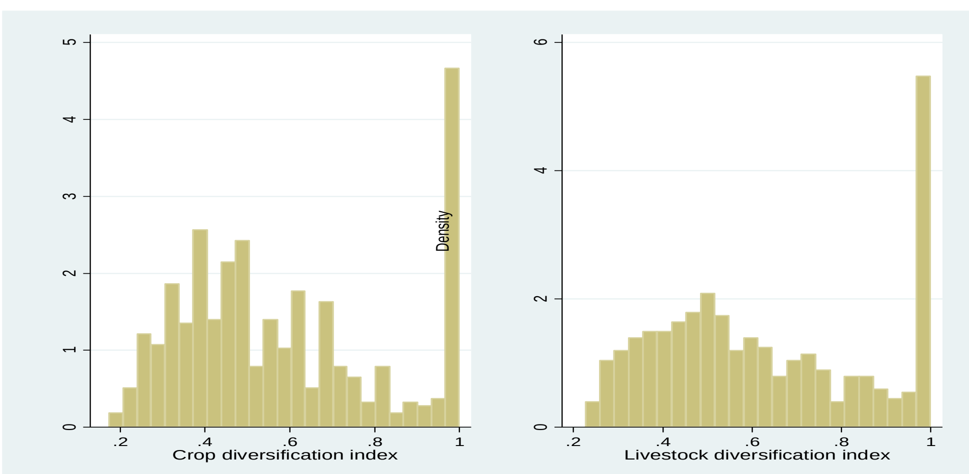


*Figure 2-2: Farm enterprise diversification indices*

A highly diversified household has an HHI close to 0, while a fully specialized one has an HHI of 1. A look at the distribution of the HHI index for both crop and livestock diversification reveals a spike around 1, indicating a high proportion with complete specialization in either of the two enterprises (Figure 2).

### 2.5.2 Exposure to climatic shocks

To establish people's exposure to climatic shocks, some studies use respondents' perceptions on long term changes in climate variables like rainfall and temperature (for example Megersa et al., 2014), while others use geo-referenced climate information (for example Asfaw et al., 2018). The former is more subjective and may be confounded by a number of factors, for example the respondent's existing knowledge about climate change. With the latter, the covariate nature of climate shocks implies that households in similar geographic locations will experience similar climatic events, hence limiting heterogeneity in the climatic shocks exposure variable.

To establish exposure to climatic shocks, our study utilizes information collected from the survey regarding whether a household was exposed to climatic shocks in the past. To construct the variable, incidences of exposure were restricted to those occurring three or more years prior to the survey year, such that the variable would be correlated with current diversification strategies as hypothesized to be, but not current food security outcomes. This allows for the validity of the variable as an instrument in estimating effect of diversification on food security, as discussed later under the section on the estimation strategy.

### 2.5.3 Access to climate information

Access to climate information has been shown to affect climate change adaptation, including farm diversification decisions (Mulwa et al., 2017; Chen 2018). The study uses data on whether households received climate-related information for both livestock and crop management to construct a climate information access variable for inclusion in the analysis. About 52% and 45% of the respondents received climate-related information on crop and livestock management, respectively. Climate information received centred on strategies that farmers could use to mitigate the effects of climatic shocks including farm enterprise diversification, adoption of resilient seeds and crops and/or livestock, etc.

While access to climate information is hypothesized to directly affect decisions to diversify farm enterprises, it is unreasonable to assume a direct effect on food security outcomes. Adoption of strategies that dampen the adverse effects of climatic shocks, as a result of a farmer being a recipient of climate information, is hypothesized to have a direct effect on household food security outcomes given occurrence of climatic shocks. Thus access to climate information is used as selection instrument, in the analysis of the effect of farm diversification on food security, within the context of a changing climate.

### 2.5.4 Food security measures

The study uses household food per capita expenditure and household dietary diversity score (HDDS) as indicators of food security. Household food expenditure measures the food access dimension of food security since it captures other sources of food besides own production, while HDDS measures the food utilization dimension. The use of the two indicators in this study ensures a comprehensive measure of food security while also acting as a check on the robustness on the results.

### 2.5.5 Socio-economic variables

Access to capital and income is an important prerequisite in the adoption of relatively expensive technology. We hypothesize a positive correlation between level of diversification and variables like access to off-farm income,, remittances, government safety nets and physical assets. These variables are also included in the outcome equation to control for their effect on food security outcomes, given the level of diversification. For the asset ownership and social capital variables included in the analysis, principal component analysis was used to construct the former and factor analysis for the latter, following Wuepper et al. (2018). Other usual household demographic variables included in the analysis include household head’s age, gender and education level, and the size of the household in adult equivalence.

## 2.6 Estimation strategy and model specification

### 2.6.1 Estimation strategy

The analytical framework presents some challenges. First, the decisions to diversify in both crop and livestock enterprises are interdependent; diversifying into different livestock types can be informed by the crop types a household farms, and vice versa. We also hypothesize that the two decisions are jointly determined by similar factors. Secondly, crop and livestock farming simultaneously affect food security either as complements or substitutes when practiced together. Analysing the effect of one without considering the other might over- or under- estimate their contribution to the food security status of a household. Similarly, different levels of diversification in each would also have different implications for food security.

Our analysis involves two decision equations with continuous dependent variables (indices with an upper limit censored at 1). The seemingly unrelated regression (SUREG) model has been used in similar studies to estimate equations with continuous dependent variables and correlated error terms (Kassie et al., 2017; Wilde et al., 1999). However, given that the dependent variables are continuous only up to an upper limit censoring, each of the two equations are re-estimated using a Tobit model and the results compared with those from the SUREG model.

In impact evaluation, the major challenge of attributing impact using observational data is establishing a true counterfactual free of bias. Observed and unobserved heterogeneity among the treatment and control groups may confound the effect of treatment, leading to wrong interpretations and policy recommendations. When observations are observed repeatedly over time intervals, panel data methods can easily be applied to control for unobserved heterogeneity, while conventional methods are used to control for the observed heterogeneity (for example observing the before and after treatment scenarios). This is not so straightforward for cross-sectional studies as in this study.

Based on the preceding discussion, our main challenge in impact estimation emanates from the non-random process of assigning treatment. Farmers in our sample may have self-selected into different levels of crop and livestock diversification, based on observable (e.g. income, extension access, etc.) and unobservable (e.g. personal ambition, managerial ability, etc.) conditions. For a genuine claim to the effect of diversification, we need to correct for this non-randomness in the diversification decisions. Existing methods that correct for this endogeneity either use instrumental variables or matching techniques like propensity score matching. In our case, the instrumental variable approach would require an instrument that is correlated with diversification decisions, but not directly correlated with food security outcomes.

Given the continuous nature of our treatments (indices of crop and livestock diversification), we rule out step-wise correction methods that assume the treatment is binary or categorical. Generalized Propensity Score (GPS) method could be used to estimate dose-response functions (for example Kassie et al., 2014) in this case on the effect of extent of farm diversification on stated food security outcomes. However, our study has two treatment variables (crop and livestock diversification indices) and estimation of the combined effect of multiple treatment variables using the GPS method is still nascent (Egger and von Ehrlich, 2013). Thus, following other similar studies (Asfaw et al., 2018; Kassie et al., 2015), we adopt the control function approach, also called the two stage residual inclusion (2SRI) method (Terza, Basu, and Rathouz, 2008), to correct for endogeneity and estimate the true effect of crop and livestock diversification on household food security outcomes.

To achieve this, we first estimate joint determinants of crop and livestock diversification using the SUREG model, and obtain the crop and livestock diversification residuals. We then plug these into a second stage Ordinary Least Squares (OLS) regression of the effect of diversification on food security, controlling for other observable covariates. The instruments used in the first stage and excluded in the second stage are access to livestock/crop management information and past exposure to climatic shocks. As stated earlier, for these variables to meet the exclusion restrictions and hence be valid instruments, they must be correlated with the diversification decisions but not food security outcomes, i.e., they should affect food security outcomes only through their effect on diversification decisions. It's intuitive to see how access to information meets this criterion. For the climatic shock exposure variable, the restriction of these shocks to those that occurred more than two years ago makes it unlikely that they are directly correlated with current food security outcomes, while being correlated with current diversification decisions. Including household income and asset ownership in the outcome equation also controls for the possible long term effects of past exposure to climate shocks, given the literature on climatic shocks and poverty traps among vulnerable households (Leichenko and Silva, 2014).

### 2.6.2 Empirical model

The SUREG model is specified as:

$$HHI_i = \beta_i climshock_i + \alpha_i climinfor_i + \Phi_i \boldsymbol{X} + \varepsilon_i \qquad (1)$$

where $HHI$ is the Herfindahl–Hirschman index for enterprise $i$ *(i=crop/livestock)*; *climshock* is the variable for climate shocks on enterprise $i$; $climinfor$ is the variable for climate information on enterprise $i$ management; $\boldsymbol{X}$ is a vector of all other explanatory variables that are similar in both equations; $\varepsilon_i$ are the error terms for the two equations and $COV(\varepsilon_1, \varepsilon_2) \neq 0$ (i.e., error terms for equations 1 and 2 are correlated).

The two equations do not need to have exactly the same set of explanatory variables (Cappellari and Jenkins, 2010). We thus include the indicator variable for climate information specific to crop management on the crop diversification equation, and that for climate information specific to livestock management on the livestock diversification equation. Climate shocks usually affect both crop and livestock enterprises within a farm, where shocks in one enterprise (e.g. livestock) may reinforce diversification in the other (e.g. crop) as a resilience-boosting strategy. To capture these dynamics, we include both shocks to crop and livestock enterprises in each of the diversification equations, including an interaction term between the two shocks. The two equations are balanced in the number of observations and are therefore estimated using the normal *SUREG* STATA command, without any loss in efficiency (McDowell 2004).

In the step-wise error correction procedure and following Wooldridge (2002), we predict the residuals from equations 1 for both livestock and crop diversification, then include them in the regression equation below:

$$FS_j = \sigma HHI_c + \pi HHI_l + \theta_i \boldsymbol{X}_i + \lambda_c + \lambda_l + \mu_i \tag{2}$$

where $FS$ is food security measure $j$ ($j$=per capita food expenditure/household dietary diversity score), $HHI_c$ and $HHI_l$ are the crop and livestock diversification indices, respectively; $\boldsymbol{X}$ is the vector of variables from equation 1; $\lambda_c$ and $\lambda_l$ are the residuals (self-selection correction terms) for crop and livestock diversification obtained from equation 1; and $\mu$ is the error term.

## 2.7 Results and Discussion

In this section, key results from the study are discussed. The section begins with describing results on the factors affecting diversification decisions, followed by results from the empirical model, and a non-parametric analysis of the effect of diversification on food security. The non-parametric analysis compares different combinations of crop and livestock diversification levels to understand how combining the two enterprises at different levels of diversification affects food security.

### 2.7.1 Determinants of diversification

The results from table 2 (columns 3 and 4) show that key drivers of adaptation are: past exposure to climatic shocks, access to information and credit, wealth (asset index and formal employment) and socio-demographic variables like household size, gender and education.

Table 2-2 Determinants of climate change adaptation strategies

| Variable | Tobit | | SUREG | |
|---|---|---|---|---|
| | Crop diversification [1] | Livestock Diversification [2] | Crop diversification [3] | Livestock Diversification [4] |
| Climate shocks-crops | 0.0173 | 0.0520* | 0.00726 | 0.0338 |
| | (0.0266) | (0.0273) | (0.0244) | (0.0227) |
| Climate shocks-livestock | 0.000868 | -0.0690** | 0.00604 | -0.0623** |
| | (0.0354) | (0.0349) | (0.0317) | (0.0296) |
| Climate shock-crops # | -0.120*** | -0.0163 | -0.102** | 0.00195 |
| climate shocks-livestock | (0.0460) | (0.0458) | (0.0415) | (0.0387) |
| Information access | -0.0895*** | -0.0368* | -0.0748*** | -0.0293 |
| | (0.0214) | (0.0215) | (0.0195) | (0.0181) |
| HH head age | -0.000778 | -7.79e-05 | -0.000576 | -8.90e-05 |
| | (0.000748) | (0.000753) | (0.000675) | (0.000629) |
| HH head education | -0.00396 | -0.00307 | -0.00354 | -0.00260 |
| | (0.00317) | (0.00317) | (0.00285) | (0.00266) |
| HH head gender | -0.0185 | -0.0591*** | -0.00637 | -0.0516*** |
| | (0.0209) | (0.0210) | (0.0190) | (0.0177) |
| HH size | -0.00508 | -0.0187*** | -0.00390 | -0.0154*** |
| | (0.00352) | (0.00357) | (0.00322) | (0.00301) |
| Formal employment | 0.0251 | -0.0396 | 0.0256 | -0.0333 |
| | (0.0242) | (0.0240) | (0.0218) | (0.0203) |
| Asset index | 0.00611 | -0.0614*** | 0.00670 | -0.0527*** |
| | (0.0113) | (0.0112) | (0.0102) | (0.00951) |
| Social capital | 0.0104 | -0.0297* | 0.00621 | -0.0231* |
| | (0.0154) | (0.0156) | (0.0142) | (0.0132) |
| Credit access | 0.106*** | - | 0.0898*** | - |
| | (0.0265) | | (0.0239) | |
| Government transfers | 0.0239 | -0.0185 | 0.0236 | -0.0137 |
| | (0.0248) | (0.0248) | (0.0225) | (0.0209) |
| Remittances | 0.0198 | -0.0295 | 0.0208 | -0.0196 |
| | (0.0222) | (0.0225) | (0.0203) | (0.0189) |
| Oshana region | 0.0225 | 0.0877*** | 0.0231 | 0.0751*** |
| | (0.0267) | (0.0272) | (0.0245) | (0.0228) |
| Oshikoto region | 0.0599** | 0.119*** | 0.0498** | 0.0981*** |
| | (0.0251) | (0.0254) | (0.0228) | (0.0213) |
| N | 639 | 639 | 639 | 639 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Consistent with other studies (Megersa et al., 2014; Rojas-Downing et al., 2017; Wuepper et al., 2018), we find that past exposure to climate shocks significantly affects both crop and livestock diversification. Farmers who experienced both crop and livestock shocks within the past ten years were found to have diversified more in both enterprises. The crop diversification variable includes area share allocated to drought tolerant millet varieties and traditional ones, in addition to other crops like legumes and nuts. As such, shocks experienced in the past could drive households to hedge against future exposure by diversifying their crop and/or variety mix. Likewise, past exposure to livestock shocks also discourages specialization in one livestock type, perhaps as a hedge against diseases and pests occasioned by climate shocks or livestock deaths due to dwindling resources like pasture and water.

Similar to other study findings (Chen et al., 2018; Mulwa et al., 2017; Shiferaw et al., 2014), availability of climate information was found to play a significant role in explaining both crop and livestock diversification. There is a negative correlation between diversification indices and information access, implying that access to information led to higher diversification (index tends to zero).

In terms of demographics, higher educated household heads diversify more in crop farming, while male-headed households are more diversified in livestock keeping. It's established in the literature that males tend to keep big ruminants like cattle, while women tend to keep small ruminants and poultry (Ellis, 1998; Gautam and Andersen, 2016). Male-headed households also tend to have both spouses present, and thus more likely to own a diversified portfolio of livestock assets. On the other hand, households that had heads who were formally employed were found to have diversified more in livestock keeping. This could indicate the importance of livestock as sources of prestige, and the ability to purchase these with access to employment wages. This is confirmed by the positive correlation between asset ownership and livestock diversification.

Consistent with other studies (e.g. Wuepper et al. 2018), the social capital variable is positively and significantly correlated with livestock diversification. Given the information used to construct this variable i.e. number of relatives and non-relatives a household has, and can rely on, in times of need for financial help, this could be viewed as a source of informal credit for acquisition of culturally important livestock assets. Some projects in the region also enhance livestock ownership by giving seed cattle to a community, which are then distributed to households within the community as the cattle multiply (Musemwa et al. 2008). Social capital within the community is expected to play a big role in livestock ownership in such cases. Surprisingly, access to credit for crop farming is found to decrease crop diversification, perhaps due to the specificity of dispensed inputs (e.g. improved millet seeds) as credit in kind.

### 2.7.2 Effect of diversification on food security

*Empirical model results*

We estimated the effect of diversification on monthly per capita food expenditure and household dietary diversity score (HDDS), conditional on other covariates controlled for in the analysis. This second stage of the 2SRI estimations followed either a Tobit or SUREG estimation of the determinants of crop and/or livestock diversification in the first stage (see Table 2). Columns 1-2 and 3-4 present estimations of the effect of crop and livestock diversification, respectively, on food security, following Tobit estimations in the first stage. Columns 5-6, on the other hand, are estimations of the effect of both livestock and crop diversification, among other control variables, on food security following SUREG estimation in the first stage. In this section, we report results from the latter estimation (columns 5-6).

The results show that both crop and livestock diversification have significant effects on food security outcomes; crop diversification significantly affects both per capita food expenditure and HDDS while livestock diversification affects only HDDS. Specifically, a unit increase in crop diversification increases household monthly per capita expenditure by about N$78 and HDDS by about 0.7 points. A unit increase in livestock diversification on the other hand increases HDDS by about 0.8 points. The results point to an income effect of crop production where greater diversification leads to higher incomes, hence ability to spend more on food, perhaps due to using resilient crops and seed varieties. Livestock in northern Namibia is mostly kept for household consumption and festivities, which could explain why diversifying in this enterprise leads to a significant effect on dietary diversity, but not in food expenditure.

Table 2-3 Determinants of food security

| | Crop divers. equations | | Livestock divers. equations | | Combined | |
|---|---|---|---|---|---|---|
| | Per capita food expenditure (N$) | Dietary diversity score | Per capita food expenditure (N$) | Dietary diversity score | Per capita food expenditure (N$) | Dietary diversity score |
| | [1] | [2] | [3] | [4] | [5] | [6] |
| Crop diversification index | -55.93*** | -0.714** | - | - | -77.62*** | -0.666* |
| | (20.19) | (0.350) | | | (19.61) | (0.339) |
| Livestock diversification index | - | - | 3.852 | -0.884** | 0.682 | -0.836** |
| | | | (29.95) | (0.381) | (29.73) | (0.367) |
| HH head age | 1.024** | 0.0142** | 1.456*** | 0.0148** | 1.437*** | 0.0136** |
| | (0.516) | (0.00577) | (0.521) | (0.00586) | (0.527) | (0.00568) |
| HH head education | 9.583*** | 0.135*** | 11.01*** | 0.117*** | 10.71*** | 0.106*** |
| | (2.307) | (0.0253) | (2.352) | (0.0279) | (2.391) | (0.0267) |
| HH head gender | 13.00 | 0.0142** | 43.16*** | 0.0104 | 50.27*** | 0.0155 |
| | (11.69) | (0.00577) | (11.99) | (0.217) | (11.92) | (0.222) |
| HH size | - | -0.00107 | | -0.0877* | - | -0.0837 |
| | | (0.0255) | | (0.0522) | | (0.0518) |
| Asset index | -2.837 | 0.173** | 33.68*** | -0.170 | 41.83*** | -0.157 |
| | (6.464) | (0.0852) | (7.656) | (0.184) | (8.861) | (0.195) |
| Social capital index | 3.460 | 0.147 | 15.55*** | -0.0922 | 18.13*** | -0.0780 |
| | (8.156) | (0.112) | (5.747) | (0.128) | (6.142) | (0.126) |
| Formal employment | 27.37** | 0.932*** | 56.72*** | 0.639*** | 64.47*** | 0.613*** |
| | (13.28) | (0.188) | (13.58) | (0.217) | (13.87) | (0.218) |
| Government transfer | -36.57*** | -0.182 | -10.64 | -0.387** | -4.893 | -0.335* |
| | (10.50) | (0.183) | (9.827) | (0.182) | (11.13) | (0.184) |
| Remittances | -12.58 | 0.371** | 3.771 | 0.194 | 5.795 | 0.245 |
| | (11.97) | (0.168) | (11.43) | (0.179) | (12.04) | (0.173) |
| Error correction term- crop | -209.8*** | 1.263 | - | - | 43.39 | 0.291 |
| | (75.51) | (1.314) | | | (98.63) | (1.533) |
| Error correction term- livestock | - | - | -486.5*** | 4.204* | -709.9*** | 4.584 |
| | | | (81.02) | (2.359) | (115.7) | (3.064) |
| Oshana region | -14.81 | -0.320 | -44.50*** | 0.0467 | -49.42*** | 0.0586 |
| | (11.11) | (0.215) | (11.83) | (0.301) | (11.90) | (0.301) |
| Oshikoto region | 14.90 | -0.368* | -31.93** | 0.128 | -37.14*** | 0.145 |
| | (15.29) | (0.199) | (14.33) | (0.339) | (13.90) | (0.335) |
| N | 639 | 639 | 614 | 614 | 613 | 613 |

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

Although the aim of the study was to evaluate the effect of diversification on food security, we report briefly on other significant variables explaining food security outcomes in our model. Socio-demographic variables that affect food security outcomes include age, education and gender of the household head. An additional year of age of the household head is associated with an increase in household monthly per capita food expenditure by about 1 Namibian dollar (N$1) and household dietary diversity score (HDDS) by about 0.01 points. Similarly, an extra year of education of the household head increases the household's monthly per capita food expenditure by about N$11 and the HDDS by about 0.11 points. Consistent with other studies (for example Tibesigwa and Visser, 2016), we find that male-headed households have higher food security status in terms of per capita food expenditure; they out-spent female-headed households by N$50 per capita on food every month.

Socio-economic variables affecting household food security include asset ownership, social capital, access to formal employment, and government transfers. Households owning more assets spend more on food, with an extra unit in the asset ownership index associated with an increase in monthly per capita food expenditure by N$42. Similarly, a unit increase in a household's social capital index increases monthly per capita food expenditure by about N$18, implying the importance of kinship ties as important safety nets in rural areas. Households in which the head is formally employed are shown to spend about N$64 on food more per household member, and have about 0.6 points more in HDDS, compared to their counterparts. This underscores the importance of diversification beyond the farm into off-farm income sources, for household food security in the face of climate change.

*A non-parametric analysis*

This subsection is a continuation of the analysis above where we attempt to see how varying combinations of crop-livestock diversification levels affect food security. To achieve this, the crop and livestock diversification indices are each divided into three categories, i.e., High, Middle and Low diversification levels, based on the distribution of each index (note that given different distributions of each index, cut-off points delineating start and end of each category may be different). The different categories from both indices are then combined to form a 3X3 matrix of crop-livestock diversification levels (Table 5). Next, food security outcomes for these different combinations are compared using kernel densities. The aim is to see whether high diversification in either crop or livestock farming is more important for household food security. Of the nine categories, our interest is thus on the food security outcomes for the low and high combinations (i.e. LL, HL, LH and HH) and results for these are reported in this section.

Table 2-4 Combinations of different levels of crop and livestock diversification

| Livestock diversification | | Crop diversification | | |
|---|---|---|---|---|
| | | $0.7 < x$ Low | $0.4 < x \leq 0.7$ Medium | $x \leq 0.4$ High |
| $0.75 < x$ | Low | ***LL*** | LM | ***LH*** |
| $0.45 < x \leq 0.75$ | Medium | ML | MM | MH |
| $x \leq 0.45$ | High | ***HL*** | HM | ***HH*** |

Six combinations are compared: Highly diversified in both crops and livestock (HH) *versus* little or no diversification in both (LL) (Figure 3a); little or no diversification in livestock and highly diversified in crops (LH) *versus* highly diversified in livestock and little or no diversification in crops (HL) (Figure 3b); highly diversified in both crop and livestock (HH) *versus* little or no diversification in livestock and highly diversified in crops (LH) (Figure 3c); highly diversified in both crop and livestock (HH) *versus* highly diversified in livestock and little or no diversifications in crops (HL) (Figure 3d); little or no diversification in livestock and highly diversified in crops (LH) *versus* little or no diversification in either (LL) (Figure 3e); highly diversified in livestock and little or no diversification in crops (HL) *versus* little or no diversification in either (LL) (Figure 3f).

As the shapes of the distribution imply, significant differences in mean expenditures are observed between HH and LL combinations (figure 3a), LH and LL combinations (figure 3e), and HL and LL combination (figure 3f). Households that are highly diversified in both crop and livestock farming (HH) on average spend more on food in a month compared to those with low diversification in both enterprises (LL). High monthly food expenditure was also noted in the low livestock-high crop (LH) and high livestock-low crop diversification (HL) categories, each compared to the low livestock-low crop (LL) diversification category.

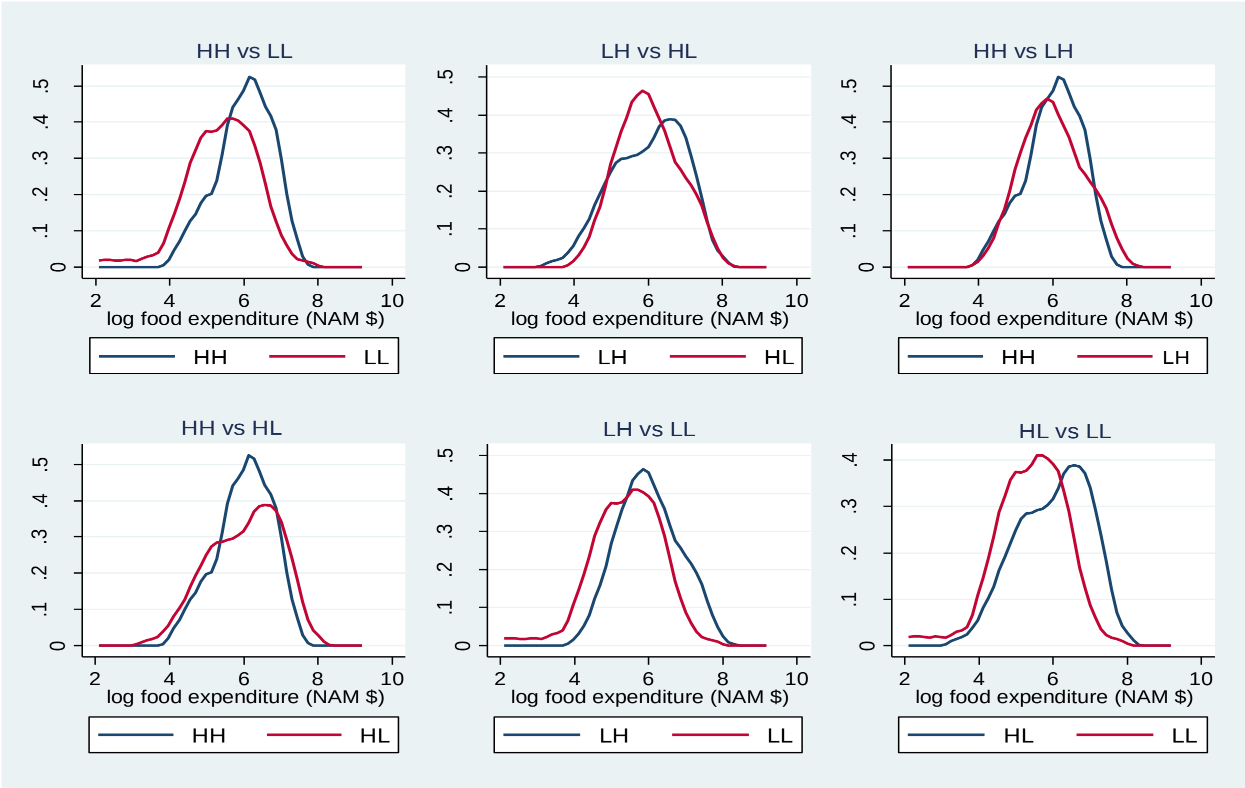


*Figure 2-3a-f (clockwise): Distributions of food expenditure for combinations of different levels of crop and livestock diversification*

No significant difference in food expenditure was observed between the low livestock-high crop (LH) and high livestock-low crop (HL) diversification categories. Similarly, the outcome for high livestock-high crop (HH) diversification category was not significantly different from that of the low livestock-high crop (LH) category or that of the high livestock-low crop (HL) categories. These results thus seem to indicate that high diversification in either crop or livestock enterprise leads to high food security outcomes, irrespective of which enterprise a household is more diversified in.

## 2.8 Conclusion and policy implications

Adapting to the changing climate is critical for rural communities residing in semi-arid regions, where livelihoods are already fragile. Diversification of livelihoods is a key strategy of strengthening the adaptive capacity and resilience of vulnerable communities. This paper finds that farm diversification has a positive impact on per capita food expenditure and dietary diversity, two indicators used as proxies for food security in this study. Further, the non-parametric analyses shows that there is no difference in food security outcomes for households that are highly diversified in either crop or livestock enterprises, and lowly diversified in the other. However, households that are highly diversified in crop and livestock enterprises achieve the highest food security outcomes.

Note that the non-parametric analysis does not control for other important factors that may also explain food security outcomes, thus the estimated effect of crop or livestock diversification on food security is not conditional on other covariates. However, combining results from this estimation with those from the parametric regression provides for robustness check. The study region is semi-arid, characterized by a mix of pastoralism and subsistence crop farming, thus external validity of results obtained in this study may not be guaranteed for areas characterized by specilized farming systems. Diversification of farm enterprises may also depend much on the availability of land resources.

Regardless of these limitations, results from the study offer important policy-relevant insights. Improving accessibility to markets is crucial for the attainment of food security, in an environment of increasing climatic shocks. Different areas may differ in the comparative advantage in terms of the agro-ecology for the production of crops or livestock. In such a case, households may thus be better off specializing in a particular enterprise, with adequate diversification within that enterprise for resilience, then accessing other food products from the markets.

Another policy variable identified in the study as a key determinant to diversification decisions is that of access to climate information related to management of both crops and livestock. Extension advice should therefore be targeted towards improving knowledge on climate change in the region, and dissemination of information on the available strategies households can utilize to mitigate against weather variability and climatic shocks like droughts. Improvement in the number of extension providers in the rural areas will also ensure many farmers have access to information on the suite of technologies and practices that constitute climate smart agriculture, for sustainable production.

The study also identifies gender as another key determinant of diversification decisions, and food security; male-headed households were more diversified in both crop and livestock enterprises, and were more food secure. Our finding suggests that female-headed households are more vulnerable, and policies that aim to empower women in the study region would therefore be beneficial. Such policies could be in the form of special financial products specifically meant for women in order to enable them access credit easier. Intervention programs by development partners that target women have also been shown to be highly effective elsewhere in improving household welfare, and should be advocated for in the study region.

Finally, the huge contribution of off-farm incomes to food security in our study further points to the already established concept of rural transformation as a vehicle for the development of rural areas in the developing world, through availing of non-farm opportunities. There is a consensus that climate change impacts will continue to be felt in the next few decades, despite the global efforts to mitigate emissions that cause the global warming problem. Policy makers in SSA thus need to urgently think of ways to fast-track access to non-farm opportunities in the rural areas of these regions, for diversified portfolio of activities that guarantee resilient livelihoods in the face of these challenges.

**References**

Adjimoti, G. O., & Kwadzo, G. T. M. (2018). Crop diversification and household food security status: Evidence from rural Benin. *Agriculture and Food Security*, *7*(1), 1–12. https://doi.org/10.1186/s40066-018-0233-x

Asfaw, S., Pallante, G., & Palma, A. (2018). Diversification Strategies and Adaptation Deficit: Evidence from Rural Communities in Niger. *World Development*, *101*, 219–234. https://doi.org/10.1016/j.worlddev.2017.09.004

Barrett, C. B., Christiaensen, L., Sheahan, M., & Shimeles, A. (2017). On the structural transformation of rural Africa. *Journal of African Economies*, *26*, i11–i35. https://doi.org/10.1093/jae/ejx009

Barrett, C. B., Reardon, T., & Webb, P. (2001). Nonfarm income diversi cation and household livelihood strategies in rural Africa: concepts, dynamics, and policy implications. *Food Policy*, *26*, 315–331. https://doi.org/10.1016/S0306-9192(01)00014-8

Barrett, C., Bezuneh, M., & Aboud, A. (2001). Income diversification , poverty traps and policy traps and shocks in Cote d’ Ivoire and Kenya shocks. *Food Policy*, *26*, 367–384. https://doi.org/10.1016/S0306-9192(01)00017-3

Berhanu, W., Colman, D., & Fayissa, B. (2007). Diversification and livelihood sustainability in a semi-arid environment: A case study from southern Ethiopia. *Journal of Development Studies*, *43*(5), 871–889. https://doi.org/10.1080/00220380701384554

Bradshaw, B. E. N., Dolan, H., & Smit, B. (2004). Farm-Level Adaptation To Climatic Variability and Change : Crop Diversification in the Canadian Prairies. *Climatic Change*, 119–141.

Cappellari, L., & Jenkins, S. (2010). The Stata Journal. *Stata Journal*, *10*(3), 288–308. https://doi.org/The Stata Journal

Chen, M., Wichmann, B., Luckert, M., Winowiecki, L., Förch, W., & Läderach, P. (2018). Diversification and intensification of agricultural adaptation from global to local scales. *PLoS ONE*, *13*(5), 1–27. https://doi.org/10.1371/journal.pone.0196392

Davis, B., Winters, P., Carletto, G., Covarrubias, K., Quiñones, E. J., Zezza, A., Zezza A., Stamoulis K., Azzarri C., & DiGiuseppe, S. (2010). A Cross-Country Comparison of Rural Income Generating Activities. World Development, 38(1), 48–63. https://doi.org/10.1016/j.worlddev.2009.01.003

Di Falco, S., Veronesi, M., & Yesuf, M. (2011). Does Adaptation to Climate Change Provide Food Security? A Micro-Perspective from Ethiopia. *American Journal of Agricultural Economics*, *93*(3), 829–846. https://doi.org/10.1093/ajae/aar006

Egger, P. H., & von Ehrlich, M. (2013). Generalized propensity scores for multiple continuous treatment variables. *Economics Letters*, *119*(1), 32–34. https://doi.org/10.1016/j.econlet.2013.01.006

Elad, Y., & Pertot, I. (2014). Climate Change Impacts on Plant Pathogens and Plant Diseases. *Journal of Crop Improvement*, *28*(1), 99–139. https://doi.org/10.1080/15427528.2014.865412

Ellis, F. (1998). Household strategies and rural livelihood diversification. *Journal of Development Studies*, *35*(1), 1–38. https://doi.org/10.1080/00220389808422553

Gautam, Y., & Andersen, P. (2016). Rural livelihood diversification and household well-being: Insights from Humla, Nepal. *Journal of Rural Studies*, *44*, 239–249. https://doi.org/10.1016/j.jrurstud.2016.02.001

Gitonga, Z. M., De Groote, H., Kassie, M., & Tefera, T. (2013). Impact of metal silos on households' maize storage, storage losses and food security: An application of a propensity score matching. *Food Policy*, *43*, 44–55. https://doi.org/10.1016/j.foodpol.2013.08.005

Government of the Repulic of Namibia. (2011). *National climate policy for namibia-2011*.

Howden, S. M., Soussana, J.-F., Tubiello, F. N., Chhetri, N., Dunlop, M., & Meinke, H. (2007). Adapting agriculture to climate change. *Proceedings of the National Academy of Sciences of the United States of America*, *104*(50), 19691–19696. https://doi.org/10.1073/pnas.0701890104

IPCC, & Pachauri, R. K. (2014). *Climate Change 2014 Synthesis Report*. *Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. https://doi.org/10.1017/CBO9781107415324

Kassie, G. W., Kim, S., & Fellizar, F. P. (2017). Determinant factors of livelihood diversification: Evidence from Ethiopia. *Cogent Social Sciences*, *3*(1), 1–16. https://doi.org/10.1080/23311886.2017.1369490

Kassie, M., Jaleta, M., & Mattei, A. (2014). Evaluating the impact of improved maize varieties on food security in Rural Tanzania: Evidence from a continuous treatment approach. *Food Security*, (2012), 1–14. https://doi.org/10.1007/s12571-014-0332-x

Kassie, M., Teklewold, H., Marenya, P., Jaleta, M., & Erenstein, O. (2015). Production Risks and Food Security under Alternative Technology Choices in Malawi: Application of a Multinomial Endogenous Switching Regression. *Journal of Agricultural Economics*, *66*(3), 640–659. https://doi.org/10.1111/1477-9552.12099

Kyalo Willy, D., Muyanga, M., & Jayne, T. (2019). Can economic and environmental benefits associated with agricultural intensification be sustained at high population densities? A farm level empirical analysis. *Land Use Policy*, *81*(May 2018), 100–110. https://doi.org/10.1016/j.landusepol.2018.10.046

Lay, J., Mahmoud, T. O., & M'Mukaria, G. M. (2008). Few Opportunities, Much Desperation: The Dichotomy of Non-Agricultural Activities and Inequality in Western Kenya. *World Development*, *36*(12), 2713–2732. https://doi.org/10.1016/j.worlddev.2007.12.003

Leichenko, R., & Silva, J. A. (2014). Climate change and poverty: Vulnerability, impacts, and alleviation strategies. *Wiley Interdisciplinary Reviews: Climate Change*, *5*(4), 539–556.

https://doi.org/10.1002/wcc.287

Makate, C., Wang, R., Makate, M., & Mango, N. (2016). Crop diversification and livelihoods of smallholder farmers in Zimbabwe: Adaptive management for environmental change. *SpringerPlus*, *5*(1). https://doi.org/10.1186/s40064-016-2802-4

Mango, N., Makate, C., Mapemba, L., & Sopo, M. (2018). The role of crop diversification in improving household food security in central Malawi. *Agriculture and Food Security*, *7*(1), 1–10. https://doi.org/10.1186/s40066-018-0160-x

Martin, S. M., & Lorenzen, K. (2016). Livelihood Diversification in Rural Laos. *World Development*, *83*, 231–243. https://doi.org/10.1016/j.worlddev.2016.01.018

McDowell, A. (2004). From the help desk: Seemingly unrelated regression with unbalanced equations. *Stata Journal*, *4*(4), 442–448. https://doi.org/The Stata Journal

Megersa, B., Markemann, A., Angassa, A., & Valle Zárate, A. (2014). The role of livestock diversification in ensuring household food security under a changing climate in Borana, Ethiopia. *Food Security*, *6*(1), 15–28. https://doi.org/10.1007/s12571-013-0314-4

Melissa Rojas-Downing, M., Pouyan Nejadhashemi, A., Harrigan, T., & Woznicki, S. A. (2017). Climate Change and Livestock: Impacts, Adaptation, and Mitigation. *Climate Risk Management*, 1–19. https://doi.org/10.1016/j.crm.2017.02.001

Mulwa, C., Marenya, P., Rahut, D. B., & Kassie, M. (2017). Response to climate risks among smallholder farmers in Malawi: A multivariate probit assessment of the role of information, household demographics, and farm characteristics. *Climate Risk Management*, *16*, 208–221. https://doi.org/10.1016/j.crm.2017.01.002

Musemwa, L., Mushunje, A., Chimonyo, M., Fraser, G., Mapiye, C., & Muchenje, V. (2008). Nguni cattle marketing constraints and opportunities in the communal areas of South Africa : Review. *Aftican Journal of Agricultural Research*, *3*(4), 239–245.

Newsham, A., & Thomas, D. (2009). Agricultural adaptation, local knowledge and livelihoods diversification in North-Central Namibia. *Tyndall Centre for Climate Change Research*, 1–48. Retrieved from http://www.tyndall.ac.uk/sites/default/files/twp140_0.pdf

Onyutha, C. (2018). African crop production trends are insufficient to guarantee food security in the sub-Saharan region by 2050 owing to persistent poverty. *Food Security*, *10*(5), 1203–1219. https://doi.org/10.1007/s12571-018-0839-7

Reid, H., Sahlen, L., Stage, J., & MacGregor, J. (2007). The Economic Impact of climate change in Namibia. *Environmental Economics Programme Discussion Paper 07-02*, (November), 1–54.

Rhoades, S. A. (1993). The Herfindahl-Hirschman index. *Federal Reserve Bulletin*, *79*, 188.

Rojas-Downing, M. M., Nejadhashemi, A. P., Harrigan, T., & Woznicki, S. A. (2017). Climate change and livestock: Impacts, adaptation, and mitigation. *Climate Risk Management*, *16*, 145–163. https://doi.org/10.1016/j.crm.2017.02.001

Shiferaw, B., Kassie, M., Jaleta, M., & Yirga, C. (2014). Adoption of improved wheat varieties and impacts on household food security in Ethiopia. *Food Policy*, *44*(October 2015), 272–284. https://doi.org/10.1016/j.foodpol.2013.09.012

Singh, C., Daron, J., Bazaz, A., Ziervogel, G., Spear, D., Krishnaswamy, J., … Kituyi, E. (2017). The utility of weather and climate information for adaptation decision-making: current uses and future prospects in Africa and India. *Climate and Development*, *0*(0), 1–17. https://doi.org/10.1080/17565529.2017.1318744

Smit, B., & Wandel, J. (2006). Adaptation, adaptive capacity and vulnerability. *Global Environmental Change*, *16*(3), 282–292. https://doi.org/10.1016/j.gloenvcha.2006.03.008

Terza, J. V, Basu, A., & Rathouz, P. J. (2008). Two-stage residual inclusion estimation: addressing endogeneity in health econometric modeling. *Journal of Health Economics*, *27*(3), 531–543. https://doi.org/10.1016/j.jhealeco.2007.09.009

Thornton, P. K., van de Steeg, J., Notenbaert, A., & Herrero, M. (2009). The impacts of climate change on livestock and livestock systems in developing countries: A review of what we know and what we need to know. *Agricultural Systems*, *101*(3), 113–127. https://doi.org/10.1016/j.agsy.2009.05.002

Tibesigwa, B., Visser, M., & Turpie, J. (2015). The impact of climate change on net revenue and food adequacy of subsistence farming households in South Africa. *Environment and Development Economics*, *20*(3), 327–353. https://doi.org/10.1017/S1355770X14000540

Tibesigwa, B., & Visser, M. (2016). Assessing Gender Inequality in Food Security among Small-holder Farm Households in urban and rural South Africa. *World Development*, *88*, 33–49. https://doi.org/10.1016/j.worlddev.2016.07.008

Tittonell, P. (2014). Livelihood strategies, resilience and transformability in African agroecosystems. *Agricultural Systems*, *126*, 3–14. https://doi.org/10.1016/j.agsy.2013.10.010

Uno, D. (2005). Farmer'S Selection of Local and Improved Pearl Millet Varieties in Ovamboland, Northern Namibia. *African Study Monographs*, *30*(March), 107–117.

Wetherald, R. T., & Manabe, S. (2002). Simulation of hydrologic changes associated with global warming. *Journal of Geophysical Research Atmospheres*, *107*(19). https://doi.org/10.1029/2001JD001195

Wilde, P. E., McNamara, P. E., & Ranney, C. K. (1999). The Effect of Income and Food Programs on Dietary Quality: A Seemingly Unrelated Regression Analysis with Error Components. *American Journal of Agricultural Economics*, *81*(4), 959. https://doi.org/10.2307/1244338

Wooldridge, J. M. (2002). Econometric Analysis of Cross Section and Panel Data. *MIT Press: Cambridge, MA, USA*. https://doi.org/10.1515/humr.2003.021

Wuepper, D., Yesigat Ayenew, H., & Sauer, J. (2018). Social Capital, Income Diversification and Climate Change Adaptation: Panel Data Evidence from Rural Ethiopia. *Journal of Agricultural Economics*, *69*(2), 458–475. https://doi.org/10.1111/1477-9552.12237

Chapter 3

# 3 The role of the emergence of large grain traders in smallholder farm markets in enhancing adoption of sustainable agricultural intensification practices in Kenya

**Abstract**

Pervasive threats of climate change and land degradation have compounded the low farm productivity problem inherent in sub-Saharan Africa. Though sustainable agricultural intensification practices have been shown to improve resilience of farm production in the face of these emerging threats, they suffer low adoption rates typical of technology adoption in these regions. Recent evidence shows the emergence of large grain traders in the smallholder farm output markets. Given established correlation between contractual farm arrangements and technology adoption, the hypothesis is that these traders can incentivize technology adoption at scale at the farm level, given their financial capacity. This study tests this hypothesis using a large panel dataset from Kenya spanning a decade. A dynamic random effects Probit model is used to evaluate how past adoption of sustainable inputs influence subsequent adoption behavior, while a control function approach is used evaluate how sales to large grain traders affect the adoption of sustainable inputs at the farm level. Results indicate that sales to large grain traders lead to higher adoption of inorganic fertilizer but not improved seed and manure, and that land ownership is a key success factor in explaining sales to these market actors. The adoption of improved seed and organic manure is persistent across time, indicating state dependence in the use of these inputs. These results suggest that strategies to foster engagements between large grain traders and farmers can enhance uptake of inorganic fertilizer; such strategies should also be accompanied by efforts to enable resource-poor farmers access to these markets.

## 3.1 Introduction

Farm yields in sub-Saharan Africa (SSA) remain low despite decades of efforts to enhance intensification in the region. This problem is amplified by increasing land degradation and the emerging threat of climate change. Consequently, there has been renewed calls for sustainable agricultural intensification aimed at increasing productivity without adverse effects to the environment (Pretty and Bharucha, 2014; Pretty et al., 2011).

Sustainable agricultural intensification practices (SAIPs) in many areas of SSA may include *inter alia*, the use of inorganic and organic fertilizers, improved seeds, measures to conserve soil and water, and farm management practices such as crop rotations involving legumes, re-incorporation of crop residues, and selective agro-forestry practices (Manda et al., 2016; Pretty et al., 2011). adoption of these practices is however highly location-specific and may vary greatly by agro-ecological conditions and relative prices of factors such as land, labor and capital.

Finding new or less utilized channels for bolstering SAIP use remains a topical issue for development economists given the ubiquitous low technology adoption problem in SSA. For the most part, policy has focused on how intervening directly into agricultural input and output markets (e.g., input subsidies and crop price supports) can nudge technology adoption. Yet it is often overlooked how changes in the broader food system can indirectly encourage intensification at the farm level. Traditionally, most smallholder farmers have sold their outputs informally to rural assembly traders and local households (Sitko and Jayne, 2014). While these actors provide market outlets for otherwise excluded farmers' in remote rural areas, their capacity and marketing model does little to directly support sustainable intensification practices by smallholder farmers. Similarly, selling to big marketing parastatals, which usually do not pay in cash, presents a challenge to the small farmer most of whom are liquidity-constrained (Olwande et al., 2015; Sitko and Jayne, 2014).

This study examines how new marketing actors in Kenya's grain value chains have affected the incentives and wherewithal of farmers to intensify their production patterns. These large grain traders (LGTs), typically do not travel to villages themselves to buy grain but buy directly from farmers at buying points in towns, hire agents who bear the LGT company name to travel to the villages to aggregate surpluses, or buy from smaller, 'satellite' traders without a formal affiliation (Burke, Jayne, and Sitko, 2019). There is a dearth of evidence on the implications of these changes in the agro-food industry on the production systems especially in the adoption of SAIPs in SSA. Most extant studies view the problem as unidirectional; how farm-level production affects marketing behavior. Emerging literature investigating effects in the opposite direction focus on how small contract farming arrangements between farmers and a particular contracting marketing actor affect farm level production decisions. Our study uses a rich panel dataset spanning a decade (2000 to 2010) to contribute to this emerging literature on backward linkage from market to production, by investigating how the entry of large grain traders (LGTs) in smallholder grain output markets in Kenya affect the adoption of sustainable intensification inputs at farm level.

## 3.2 Literature review

The functioning of output markets, including the attributes of marketing actors, may influence farm behavior in numerous ways. For example, reliable and timely cash payments for farm outputs may relax future binding liquidity constraints that otherwise dampen adoption of intensification inputs. Evidence indicates that under favorable conditions, outgrower cash crop programs have encouraged greater farmer use of inputs in food crop farming (Govereh and Jayne, 2003). This is through exploitation of the synergy between the two crop types, such that even though food crops may not be highly marketed, farmer exposure to the market through cash crop overcomes liquidity constraints on the purchase of cash inputs for food production too.

Much of extant literature that relates the leveraging of the markets for farm-level productivity is in on contract arrangements. Across SSA, buyers of cash crops like coffee, tea and horticultural crops provide farmers with inputs and advisory services and in return are guaranteed quality output. Minten (2010) found that smallholder farmers in Madagascar receiving inputs from processors through contract arrangements increased their yields significantly when this was combined with advice from technical assistants. In Ethiopia, potato farmers were found to prefer contract arrangements since these insured them against uncertainty in the input markets (Abebe et al., 2013). Several recent studies also find that contract farming arrangements lead to enhanced intensification, and an improvement in welfare for the participating farmers (Bellemare, 2012; Maertens and Vande Velde, 2017; Ton, et al., 2018).

While this literature relates to small scale, low volume contractual arrangements between a producer(s) and a group of farmers where farmers are engaged in one project at a time, the question is whether similar benefits can trickle down to farmers through other market actors who are not engaged in contractual arrangements with farmers. Recent evidence shows that large-scale grain traders (LGTs) have rapidly expanded their operations and become an important direct and indirect buyer of grain for smallholder farmers in many parts of the region (Sitko and Chisanga, 2016; Sitko et al., 2017). These LGTs are similar in scale to the market actors that enter into contractual farming arrangements with smallholder farmers, in terms of output demand and capital. While there are no formal contractual arrangements between these large market actors and farmers, it is interesting to assess how their operations may be transforming the food production systems over time. This is especially so since their operations have a potential to reach a large unspecified number of farmers, unlike contractual arrangements that happen within a smaller scale between a market player and a specific group of farmers. Using a panel dataset spanning a decade, this study adds to the literature on the role of market actors in enhancing farm production by looking at how LGTs affect take up of sustainable intensification inputs.

## 3.3 Data

### 3.3.1 Data sources

Data used in this study comes from the Tegemeo Institute rural households panel data project, a collaborative effort between Egerton University's Tegemeo Institute and Michigan State University. The dataset runs from 1997 to 2010 and covers 24 Districts in Kenya within which there are 39 Divisions and 120 villages (due to inadequate definition of the key variable used in this study in 2010 i.e. sales to LGTs, the study uses data running from 2000 to 2010). A stratified sampling technique was used to take into account the ecological diversity in the country where all the districts were classified into eight agro-regional zones based on agro-climatic conditions, agricultural activities and rural livelihoods. Using standard proportional sampling, 1,600 farm households were then sampled randomly from the 24 districts. Of these, 1,512 households were interviewed in 2000 and 1,309 in 2010. Attrition across the waves was thus relatively small and largely random (Jin and Jayne, 2013). The study uses this unbalanced panel data across the years in the analysis.

A standard question put to the respondents across the four waves regarded where the household had sold their largest part of their grain (maize, wheat and rice) output after harvesting, with large traders being one of the options under consideration. This question was used to construct the key treatment variable of whether a household sold a large share of their grain to a large trader or not (=1 if the household sold to LGT, and 0 in otherwise). We acknowledge the limitation on definition of this variable since we rely on farmers themselves to identify the type of trader that they sold their grain to. To minimize errors in the measurement of the variable, adequate training was provided to the enumerators to help the respondents identify the trader-types using a three check criteria; the volume of grain bought, whether the trader comes to buy for himself or uses buying agents, and lastly, whether the trader operates under a company name (Burke et al., 2019). It is also worth noting that results from a study carried out in 2016 on LGTs in Kenya to understand their involvement in the smallholder grain markets (Sitko et al., 2017) largely correspond to this paper findings and increases our confidence in the correct identification of these market actors by the farmers. Future studies on this aspect however may need to find a more robust way of identifying these actors. In addition, the use of the proportion of sales sold to the LGTs may be a better outcome variable, rather than the binary indicator variable used in this study, given data availability.

The outcome variables considered in the study are the sustainable agricultural intensification inputs (SAIPs) which include inorganic fertilizer, improved seed and organic manure. Again, these variables were constructed from standard questions in all survey waves about household use of the SAIP. Data for manure use in the 2000 wave is however missing and only three waves were used in the analysis of the demand for this particular SAIP.

### 3.3.2 Description of variables

Table 1 presents the descriptive statistics of variables used in this study. These are described in detail in the following section.

Table 3-1 Summary statistics

| Variables | 2000 (N=1,512) | | 2004 (N=1,397) | | 2007 (N=1,342) | | 2010 (N=1,309) | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. |
| *Dependent variables* | | | | | | | | |
| Fertilizer use (1=Yes) | 0.66 | 0.473 | 0.71 | 0.453 | 0.76 | 0.428 | 0.75 | 0.434 |
| Fertilizer quantity (kg) | 206 | 398.6 | 190 | 333.9 | 200 | 340.1 | 169 | 263.8 |
| Fertilizer use kg/acre | 90.0 | 306.90 | 83.0 | 326.0 | 82.3 | 288.52 | 76.9 | 118.44 |
| Improved seed use (1=Yes) | 0.66 | 0.473 | 0.67 | 0.472 | 0.73 | 0.445 | 0.82 | 0.381 |
| Manure use (1=Yes) | - | - | 0.74 | 0.438 | 0.77 | 0.422 | 0.78 | 0.415 |
| Manure quantity (kg) | - | - | 1815 | 3146.7 | 1463 | 2494.6 | 1251 | 2002.4 |
| *Explanatory variables* | | | | | | | | |
| Large Grain Trader sales (LGTs) (1=Yes) | 0.015 | 0.1197 | 0.007 | 0.0843 | 0.085 | 0.2789 | 0.095 | 0.2929 |
| Non-self-proportion of LGT sellers in district | 1.44 | 2.487 | 0.71 | 1.08 | 8.34 | 10.82 | 9.32 | 12.285 |
| Distance to extension (Km) | 5.7 | 7.01 | 5.3 | 5.81 | 4.6 | 5.07 | 5.4 | 5.13 |
| Age of hh head (years) | 53.1 | 13.97 | 56.4 | 13.57 | 58.6 | 13.42 | 60.5 | 13.22 |
| Gender of hh head (1=Female) | 0.13 | 0.332 | 0.21 | 0.404 | 0.24 | 0.426 | 0.27 | 0.444 |
| Education of hh head (years) | 6.0 | 4.48 | 6.7 | 5.48 | 8.0 | 3.99 | 8.1 | 4.02 |
| Credit constrained (1=Yes) | 0.04 | 0.197 | 0.08 | 0.266 | 0.02 | 0.138 | 0.02 | 0.140 |
| Total asset value (‘00000Ksh) | 1.84 | 3.746 | 2.60 | 11.300 | 3.08 | 9.839 | 3.61 | 8.380 |
| Own cultivated land (acres) | 3.52 | 4.655 | 3.57 | 7.602 | 3.29 | 7.017 | 2.82 | 4.278 |
| Village level fertilizer price at planting time (ksh/kg) | 27.8 | 3.40 | 30.4 | 4.70 | 37.3 | 3.51 | 55.2 | 10.04 |
| Av. annual rainfall (mm) | 608 | 261.7 | 722 | 269.8 | 615 | 202.0 | 430 | 194.7 |
| *Agro-ecological zones controls (%)* | | | | | | | | |
| Coastal Lowland | 5.95 | | 6.30 | | 6.26 | | 6.34 | |
| Lowland | 7.94 | | 3.58 | | 3.58 | | 3.44 | |
| Lower Midland 3-6 | 19.11 | | 19.97 | | 19.67 | | 19.56 | |
| Lower Midland 1-2 | 10.98 | | 11.24 | | 11.18 | | 11.23 | |
| Upper Midland 2-6 | 18.92 | | 19.40 | | 19.52 | | 19.56 | |
| Upper Midland 0-1 | 16.87 | | 17.75 | | 18.26 | | 18.49 | |
| Lower Highland | 17.53 | | 18.83 | | 18.48 | | 18.26 | |
| Upper Highland | 2.71 | | 2.93 | | 3.06 | | 3.13 | |

*Sustainable intensification inputs*

Fertilizer is a critical sustainable intensification input, replenishing soil nutrients thus preventing nutrient mining and land degradation. In this study, fertilizer use as a dependent variable is measured by the proportion of households in the sample using the input, as well as the intensity of use. The latter is informed by literature that shows that though many households may be using fertilizer, a majority of these do not use the recommended rates of the input (Kihara et al., 2016; Sheahan, Black, & Jayne, 2013). Results point to a general increase in the proportion of farmers using fertilizer from 66% in 2000 to 76% and 75% in 2007and 2010, respectively. In terms of intensity of use, farmers used 200kg of fertilizer on average in 2000, with the rate falling to about 170kg in 2010.

Improved seed allows for the realization of higher outputs per unit of labor and land and is therefore an important sustainable intensification input. This explains its choice for a dependent variable in our study. The results show a steady increase in the proportion of farmers using the input from 66% in the year 2000 to over 80% in the year 2010.

Organic fertilizer has been show to increase soil carbon and help soils capacity to utilize inorganic fertilizers (Marenya & Barrett, 2009). This is thus a critical sustainable intensification input ad justifies its inclusion as an outcome variable in our study. While our study lacks the data for the input use for 2000, results show that on average, households used about 1800kg and 1200kg of the input in 2004 and 2010 respectively.

*Large grain trader sales*

The key explanatory variable is an indicator whether a household sold to large traders in a season. Controlling for other confounders, we hypothesize that households that sell to large traders are more likely to invest in sustainable intensification inputs, following the conceptualized pathways discussed earlier in this pare i.e. higher prices for produce, credit facilities, knowledge sharing, etc. Table 1 show the proportion of these type of traders jumping from about two percent in 2001 to ten percent in 2010. The transition matrix in Table 2 shows how farmers enter and exit the LGT market across the waves. The results show significant movement in the proportion of farmers entering and exiting the LGTs market. Of the farmers who were selling to LGT in 2000, only five percent of these were still selling to LGTs in 2004 with the rest exiting the market (95%) in same time period. These initial LGT sellers however come back to the market with 23% and a further 43% of the farmers who sold to LGTs in 2000 doing so again in 2004 and 2007, respectively. Likewise, about one percent of the farmers who did not sell to LGT in 2000 entered the market in 2004 and the proportion grew to eight and nine percent of new entrants in 2007 and 2010, respectively.

Table 3-2 A transition matrix of LGT sales across the panel

| | | LGT seller (%) | | | Non- LGT seller (%) | | |
|---|---|---|---|---|---|---|---|
| | | 2004 | 2007 | 2010 | 2004 | 2007 | 2010 |
| LGT seller (%) | 2000 | 4.6 (1) | 22.7 (5) | 42.9 (9) | 95.4 (21) | 77.3 (17) | 57.1 (12) |
| | 2004 | | 11.1 (1) | 11.11 (1) | | 88.9 (8) | 88.9 (8) |
| | 2007 | | | 31.8 (35) | | | 68.2 (75) |
| Non- LGT seller (%) | 2000 | 0.6 (8) | 8.2 (106) | 8.9 (112) | 99.4 (1330) | 91.8 (1,181) | 91.1 (1144) |
| | 2004 | | 8.5 (113) | 9.5 (123) | | 91.5 (1220) | 90.5 (1177) |
| | 2007 | | | 7.4 (89) | | | 92.6 (1110) |

N in parenthesis

The results also show that a large proportion of the farmers who did not sell to LGTs in 2000 remain outside this market segment, with 99.4% of these still not selling to LGTs in 2004. This proportion however reduces to 91.8% and 91.1% in 2007 and 2010 respectively, after a few new entrants into the LGT market in these years. The results show some stability in later waves, where 31.8% of the farmers who sold to LGTs in 2007 still do so in 2010, with68.2% exiting the market over the same time period. This is significant especially since the proportion of new entrants is growing in the same time period.

*Other covariates*

Institutional, financial and physical infrastructure are key determinants of technology diffusion and have been used ubiquitously in studies similar to ours. In this study, distance to extension in is used as an indication of access to extension advice, while questions on need for, and lack of (inadequate) access to needed credit, are used to construct a credit constraint variable, as an indication of whether a household was credit constrained or not. The hypothesized correlation between credit constraint and SAIP adoption is thus negative. Total asset value is used to control for household wealth, which could also affect the likelihood of adopting SAIPs. The survey also asked for village level prices of inorganic fertilizer at planting time, and this variable is included in the analysis of fertilizer demand since cost of inorganic fertilizer has been identified as a key constraint to adoption and use rates of the input (Sheahan, Black, & Jayne, 2013).

Land ownership is also important for two reasons; first, it is an important economic indicator in the rural areas, and secondly, the amount of land a household cultivates determines the quantity of an intensification input to use. The results in Table 1 show that the amount of cultivated land controlled by households is gradually decreasing, from about 3.5 acres in 2001 to 2.8 acres in 2010, indicating increasing land pressure as population density increases. The age, gender and education of heads of households have been shown to explain technology adoption, and are included in the study as additional control variables.

A variable capturing the average annual rainfall (mm) experienced at cultivated plot is also included to control for annual variation in rainfall across regions. The use of SAIPs could vary from region to region depending on the agricultural potential, which might also be affected by shocks across time. Fertilizer demand has for example been shown to be elastic to profitability, which is in turn affected by prevailing productivity conditions. Controlling for rainfall in estimating the demand for SAIPs is thus instructive given that most smallholder production in the region is rain-dependent.

### 3.4 Estimation strategy and empirical models

This study investigates the effect of LGT sales on farmers' likelihood of adopting a sustainable agricultural intensification input (SAIP). The decision to adopt a SAIP is partly explained by unobserved idiosyncratic factors like risk attitudes and ambition, which could also be correlated with the explanatory variables like in this case, the decision to sell to LGT. Access to panel data presents an opportunity to study important dynamics in input adoption. For example, the role of intensification inputs on productivity enhancement is uncontested in the literature. Thus, the adoption of a SAIP in one season can lead to higher incomes, which potentially relaxes liquidity constraints and enhance SAIP take up in subsequent periods. Likewise, some treatment effects are persistent. For example, Sitko et al (2018) found that farmers selling maize to a large grain trader obtained about six percent higher farm-gate price for maize than farmers selling to other types of buyers, controlling for market access conditions and month of sale. Households selling to a LGT may therefore obtain greater revenue from their output, enabling them to purchase more cash inputs or hire labor in subsequent seasons to utilize labor-intensive SAIPs, and/or foster formal or informal CFAs that enable them to get inputs on credit in subsequent seasons

Model selection in panel data analysis is guided by researcher assumptions regarding unobserved heterogeneity. In the case where there is correlation between the explanatory variables at time $t$ ($\boldsymbol{X}_t$) and the error term at time $t$ ($\mu_t$) , or explanatory variables at time $t$ ($\boldsymbol{X}_t$) are correlated with past period's error term ($\mu_{t-1}$), a pooled OLS estimator will be inconsistent. If only the latter is assumed to hold, a random effects (RE) estimator will be consistent but if the first and/or second case is assumed, only the fixed effects (FE) estimator will be consistent (Wooldridge, 2002). The FE method is problematic to use with non-linear models though since it involves subtracting the means of time-varying variables across $T$ $(1 \ldots T)$ for each individual from the observed variable values at $t$. Time-invariant variables like gender and education of head also drop out of the analysis when using this method.

We adopt various models and functional forms that control for these issues, discussed in following subsections. First, we use a dynamic Probit model that analyzes the dynamic process of SAIPs adoption, while controlling for unobserved characteristics and initial conditions problem. This model assumes that there is no endogeneity between our key variable, LGT sales and the outcome variables, sustainable agricultural intensification inputs (SAIPs) adoption. This naïve assumption is used to test for dynamism in SAIPs adoption, and not causation between LGT sales and SAIPs adoption. Next, we make a more reasonable assumption of non-randomness in treatment (LGT sales) and adopt the control function approach to account for this. Lastly, we recognize the fact that demand for certain SAIPs like inorganic fertilizer is not necessarily linear; first, a farmer decides whether to use or not, given prevailing circumstances, then decides on how much to use. We thus adopt a Double Hurdle functional form to account for this corner solution problem.

### 3.4.1 The dynamic random effects Probit model

The conceptual model for SAIPs adoption can be represented as;

$$y_{it}^{*} = \alpha_i LGT_{it} + \beta_i \boldsymbol{X}_{it} + k_i + u_{it} \qquad (1)$$

where $y_{it}^{*}$ is a latent indicator of SAIP adoption ($y_{it}$=1 if adopted and 0 otherwise) by household $i$ in time period *t*; LGT is the indicator variable of interest i.e. if the household had LGT sales in year *t*; $X_{it}$ is a vector of exogenous variables that explain SAIP adoption like gender, access to information, employment status etc.; $k_i$ is a unit-specific time-invariant unobserved effect; and $u_{it}$ is an idiosyncratic error term.

To capture the dynamic adoption process, we include lags of dependent variables as additional regressors;

$$y_{it}^{*} = \gamma y_{it-1} + \alpha_i LGT_{it} + \beta_i \boldsymbol{X}_{it} + k_i + u_{it} \qquad (2)$$

where $y_{it-1}$ represents past SAIPs adoption decisions; Even if we assumed that $Cov\ (\mu_t, X_t) = 0$ from equation 1, this cannot hold in equation 2. This is since errors in past time periods $u_{it-1}$ are correlated with current ones $u_{it}$, by inclusion of the lagged variables. A pooled OLS would be inconsistent in this case.

In the case where key explanatory variables are not expected to vary much, FE estimators lead to imprecise estimates (Wooldridge, 2002 pp 286). The key determinants to SAIPS use are hypothesized to be age, gender and education of household head, all of which are time constant across the panel. The key explanatory variable may also not vary much since only about two percent of farmers sell to LGTs out of the total sample in 2000, with this proportion raising to about ten percent in 2010; a large proportion of farmers therefore remain in the counterfactual group of "non-sellers to LGTs" from year to year. A fixed effects estimator may therefore not be best suited for our analysis due to the incidental parameter problem. Likewise, it’s not plausible to assume that the unobserved heterogeneity in our model is orthogonal to all the explanatory variables (thus satisfying the exogeneity assumption), based on the preceding discussion earlier in this section. Thus, a random effects estimator would also yield inconsistent estimates. Empirical studies facing this issue (for example Muyanga et al., 2013) use the correlated random effects (CRE) framework to overcome the shortcomings of both the FE and RE estimators.

In the CRE framework, the unobserved heterogeneity is modelled as;

$$k_i = \alpha_0 + \alpha_1 \overline{LGT}_i + \alpha_2 \overline{\boldsymbol{X}}_i + a_i \tag{3}$$

Where $k_i$ is the time-invariant household-specific unobserved heterogeneity; $\overline{LGT}_i$ and $\overline{\boldsymbol{X}}_i$ represent the means of time-varying explanatory variables across $T\ (t = 1, \dots, T)$; and $a_i$ is the household-specific error term. Our analysis follows this framework to correct for unobserved effect.

By including lagged depended variable to study dynamics in sustainable agricultural intensification inputs (SAIPs) adoption, we introduce a potential bias where the unobserved heterogeneity as modelled above could be correlated with the initial observation, $y_{i0}$. The assumption being made here is that the stochastic dynamic process started when the households in the sample were observed in the first period ($t_0$). This is unreasonable since if we are assuming a dynamic process with previous behavior informing subsequent decisions, then adoption of SAIPs prior to $t_0$ should also affect adoption decisions within the panel period. These effects will be captured in the unobserved heterogeneity and need to be controlled for, for a genuine estimation of state-dependency in SAIPs adoption.

### 3.4.2 Controlling for initial conditions in the unobserved heterogeneity

Rabe-Hesketh and Skrondal (2013) show that Wooldridge's (2005) simple solution of modelling the distribution of the unobserved heterogeneity conditional on the initial values might result in serious bias when used with constrained models that includes the means of time-varying explanatory variables, like the CRE above. The solution suggested by Rabe-Hesketh and Skrondal (2013) was that of including the initial-period explanatory variables as additional regressors in modelling the unobserved heterogeneity. This solution was shown to be more efficient in the case of short panels, like in our case.

This study thus adopts the CRE framework where the unobserved heterogeneity is modelled by including within-means of time-varying variables, then adding the values of the explanatory variables at the first wave of the panel, to control for the initial conditions problem following Rabe-Hesketh and Skrondal (2013). From equation 3, the unobserved heterogeneity is thus adjusted to:

$$k_i = \alpha_0 + \alpha_1 y_{i0} + \alpha_2 \overline{LGT}_i + \alpha_3 LGT_{i0} + \alpha_4 \overline{\boldsymbol{X}}_i + \alpha_5 \boldsymbol{X}_{i0} + a_i \tag{4}$$

where $y_{i0}$, $LGT_{i0}$, and $\boldsymbol{X}_{i0}$ represent values for sustainable agricultural intensification inputs (SAIPs), LGT sales, and other time-varying explanatory variables at $t_0$, respectively; $\overline{LGT_i}$ and $\overline{\boldsymbol{X}}_i$ are the means of the time-varying explanatory variables across *T (t=0,…T)* for each $i$ such that $\overline{LGT_i} = {}^1/_T \sum_{i=0}^{T} LGT_{it}$ and $\overline{\boldsymbol{X}}_i = {}^1/_T \sum_{i=0}^{T} X_{it}$; and $a_i$ is the normally distributed household-specific error term with zero mean and variance $\delta_a^2$.

Replacing for $k_i$ in equation 2 and holding the assumption that the term captures the unobserved heterogeneity, $y_{it-1}$ can then be interpreted to capture the genuine state dependence of SAIPs adoption on past adoption behavior. The equations are then estimated in STATA using the command developed by Grotti and Cutuli (2018). For comparative purposes, we also estimate equation 2 (where we assume there is no unobserved heterogeneity in our model) and report these results.

### 3.4.3 Non-random selection into large-grain-trader markets

The dynamic model described above explains how marketing behavior may influence SAIPs adoption decisions, controlling for time-invariant unobserved characteristics and the initial conditions problem in dynamic models. It could also be the case that there are time-varying unobserved variables that cannot be controlled for by the above procedure. A valid concern may be whether this adequately controls for the obvious self-selection problem; farmers endowed with assets like land are able to generate high outputs, thus have the economies of scale to sell to LGTs. While our hypothesis is that selling to LGTs enable farmers to utilize SAIPs more, it could as well be the case that using SAIPs enables a farmer to generate higher outputs, which then enables them to participate in markets where volume of sales may matter, like LGT markets.

The control function approach has been used in studies similar to ours to solve this problem (Asfaw, Pallante and Palma, 2018; Ricker-Gilbert, Jayne, and Chirwa, 2011). The approach requires an instrumental variable (IV) that should be correlated with the potentially endogenous variable but not correlated with the error term in the structural model when conditioned on other covariates. In our case, we use the non-self-proportion of farmers in a district selling to LGTs as an instrument in the reduced form equation, which is then excluded in the structural fertilizer demand equation. The number of other farmers residing in the same district that are selling to LGTs would also inform the decision of a particular farmer to sell to these market actors. Accessibility of these LGTs in town markets within the district, the production potential in the district, land ownership dynamics in district would all reasonably imply farmers within such districts would sell to LGTs, given other farmers doing within the district. There is also little reason to believe that after conditioning on other covariates, the non-self-proportion of farmers selling to LGTs in the district would be directly correlated with the error term in the fertilizer demand equation, except through the reduced form equation, thus satisfying the exogeneity assumption.

Unlike in the previous dynamic random effects Probit model where we adopted a binary indicator of SAIPs adoption, we now shift the analysis to consider continuous dependent variables for manure and inorganic fertilizer. The literature indicates that sub-optimal use of fertilizer leads to yield stagnation (see for example Sheahan, Black, and Jayne, 2013). Thus, while a farmer may be using the input, they might be using less than the optimal quantity resulting in low yields. This motivates the shift from binary indicators of organic and inorganic fertilizer use to total quantities used in kilograms. To complete the analysis and following the conceptualization that LGTs sales in a particular year may not necessarily affect SAIP use that year but in subsequent ones, which in turn enhances future likelihood of selling to LGTs and using SAIPs, we include lagged SAIPs use/demand to capture this dynamism.

We implement the following equation in the first stage;

$$LGTs_{it}^{*} = \Omega_i PrLGTs_{dt} + \beta_i \boldsymbol{X}_{it} + \sigma_i \overline{\boldsymbol{X}}_i + \mathcal{E}_{it} \qquad (5)$$

where $LGTs_{it}^{*}$ is the latent indicator if a household *i* sold to LGTs in year *t*; $PrLGTs_{dt}$ captures the non-self-proportion of farmers selling to LGTs in district *d* at year *t*; $\boldsymbol{X}_{it}$ is a vector of exogenous explanatory variables; $\overline{\boldsymbol{X}}_i$ are the Mundlak augmenting means of time-varying explanatory variables; and $\mathcal{E}_{it}$ is the idiosyncratic error term.

Residuals from the first stage are included in the following second stage regression for improved seed use and quantity of manure used;

$$y_{it}^{*}/y_{it} = \gamma y_{it-1} + \alpha_i LGT_{it} + \theta_i \widehat{LGT_{it}} + \beta_i \boldsymbol{X}_{it} + \overline{LGT}_i + \sigma_i \overline{\boldsymbol{X}}_i + \mathcal{E}_{it} \qquad (6)$$

Where $y_{it}^{*}/y_{it}$ is binary indicator of improved seed use and quantity of manure in kilograms, respectively; $y_{it-1}$ captures lagged dependent variable; $\widehat{LGT_{it}}$ is the residual term obtained from equation 5; and $\mathcal{E}_{it}$ is the idiosyncratic error term; the other terms are as defined before.

### 3.4.4 The corner solution problem in fertilizer adoption

The control function approach discussed above, and the inclusion of Mundlak means of time-varying variables as additional covariates, control for endogeneity issues in estimating SAIPs adoption. An additional challenge in analyzing sustainable agricultural intensification inputs (SAIPs) demand is the issue of separate decisions on whether to use a particular SAIP, and how much of the SAIP to use. This is especially so in the case of inorganic fertilizer where a large percentage of farmers do not use the input, hence a non-trivial number of zero outcomes in the dependent variable.

Functional forms that account for this nonlinearity in demand of inorganic fertilizer include the Double Hurdle and Type 1 Tobit models. While the former is more flexible in the assumptions of the decision process in the two hurdles (i.e. whether to use fertilizer or not, and how much to use), the latter is more restrictive and assumes the two decisions are determined by the same process, hence giving less attention the first hurdle. We follow Croppenstedt, Demeke and Meschi (2003) and Ricker-Gilbert, Jayne, and Chirwa (2011) in using the double hurdle model for panel data to analyze fertilizer demand, following Engel & Moffatt (2014).

Equation 6 for fertilizer demand is thus broken into two for the two hurdles; hurdle 1 is a Probit estimation of the probability of a household using fertilizer i.e.

$$Fert_{it}^{*} = \varphi Fert_{it-1} + \Omega_i DExt_{it} + \alpha_i LGT_{it} + \theta_i \widehat{LGT_{it}} + \beta_i \boldsymbol{X}_{it} + \overline{LGT}_i + \sigma_i \overline{\boldsymbol{X}}_i + \mathcal{E}_{it} \qquad (7)$$

where $Fert_{it}^{*}$ is the latent indicator of fertilizer use; $DExt_{it}$ is household *i* distance to extension advice, which is used as the selection instrument for the identification of the model; and the other terms are as defined in equation 6.

The second hurdle is specified as;

$$Fertkg_{it} = \omega Fertkg_{it-1} + \alpha_i LGT_{it} + \theta_i \widehat{LGT_{it}} + \beta_i \boldsymbol{X}_{it} + \overline{LGT}_i + \sigma_i \overline{\boldsymbol{X}}_i + \delta IMR + \mathcal{E}_{it} \qquad (8)$$

where $\mathrm{Fertkg_{it}}$ is quantity of fertilizer used in kg; $Fertkg_{it-1}$ is the lagged demand for fertilizer; *IMR* are the inverse mills from the first hurdle (equation 6); and the other terms are as defined before.

## 3.5 Results

In this section, results from the described models in section 3 are presented. First, we present the dynamic random effects Probit results, followed by results from the first stage of the control function approach. The second stage results are presented next, starting with the double hurdle estimation of fertilizer demand, followed by those from a Probit and OLS estimation of improved seed and manure adoption, respectively.

### 3.5.1 Dynamic random effects Probit model results

For comparative purposes, we present results from pooled Probit regressions (equations 1) and the random effects dynamic Probit model (equations 2). Only results from the random effects dynamic Probit model are discussed in this section. The results show that previous adoption of all SAIPs except inorganic fertilizer affect current adoption status suggesting sustainability in the adoption of these SAIPs, perhaps given the relatively lower costs of seed and manure (usually from own production) compared to fertilizer. LGT sales are positively correlated with fertilizer use and improved seed but not manure. This result could imply the significant role that LGTs play in enabling households to access relatively expensive inputs like fertilizer and improved seed. The above results are further interrogated using the control function approach and results are presented in the subsequent section.

Table 3-3 Results from Pooled and random effects dynamic Probit models

| | Equations 1 | | | Equations 2 | | |
|---|---|---|---|---|---|---|
| | Fertilizer | Improved seed | Manure | Fertilizer | Improved seed | Manure |
| Lag. dependent variable | 1.517*** | 1.302*** | 0.962*** | 0.126 | 0.396*** | 0.539** |
| | (0.130) | (0.0931) | (0.202) | (0.191) | (0.144) | (0.211) |
| LGT sales | 0.327 | 0.620*** | -0.194 | 0.932*** | 0.532* | -0.0190 |
| | (0.199) | (0.226) | (0.132) | (0.307) | (0.323) | (0.203) |
| Distance to extension | -0.0220*** | -0.00759 | -0.00830 | -0.0271*** | -0.00245 | -0.00542 |
| | (0.00717) | (0.00610) | (0.00868) | (0.0102) | (0.00841) | (0.00765) |
| HH age | 0.00891*** | -0.00526** | 0.00163 | 0.0114 | -0.0145 | -0.0111 |
| | (0.00315) | (0.00259) | (0.00327) | (0.0126) | (0.00923) | (0.0108) |
| HH gender | -0.212** | -0.259*** | -0.155 | -0.299* | -0.315*** | -0.142 |
| | (0.0853) | (0.0769) | (0.110) | (0.154) | (0.120) | (0.102) |
| HH education | 0.0401*** | 0.0157* | 0.00325 | 0.0429** | 0.000434 | -0.00559 |
| | (0.0113) | (0.00830) | (0.0107) | (0.0178) | (0.0123) | (0.0120) |
| Credit constrained | -0.326** | -0.133 | 0.0121 | -0.645*** | -0.172 | 0.0338 |
| | (0.164) | (0.148) | (0.324) | (0.238) | (0.196) | (0.314) |
| Asset value (‘00000Ksh) | -0.0189* | 0.0185 | 0.0263* | -0.0509*** | -0.0157 | -0.00230 |
| | (0.0103) | (0.0128) | (0.0148) | (0.0185) | (0.0131) | (0.0138) |
| Own cultivated land (acres) | 0.0294** | 0.0399*** | -0.0193 | 0.0518 | -0.00399 | -0.0267 |
| | (0.0137) | (0.0131) | (0.0143) | (0.0350) | (0.0285) | (0.0247) |
| Av. village Fertilizer price (Ksh/kg) | 0.000695 | - | - | -0.00400 | - | - |
| | (0.00464) | | | (0.00623) | | |
| Av. annual rainfall (mm) | 0.000236* | 0.000271** | -0.000374 | 0.000858*** | 0.000715*** | -0.000174 |
| | (0.000141) | (0.000132) | (0.000237) | (0.000259) | (0.000186) | (0.000202) |
| AEZ controls | YES | YES | YES | YES | YES | YES |
| Year controls | YES | YES | YES | YES | YES | YES |
| Mundlak means | NO | NO | NO | YES | YES | YES |
| Initial conditions | NO | NO | NO | YES | YES | YES |
| N | 3,430 | 3,430 | 2,094 | 3,430 | 3,430 | 2,094 |

Robust standard errors in parentheses

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

Among the socio-demographic variables and consistent with many others studies, the results show that female-headed households are less likely to adopt inorganic fertilizer and improved seed while households with higher educated household heads are more likely to use inorganic fertilizer. On the other hand, credit constrained households and those that are far from extension extension advice are less likely to use fertilizer. Lastly, more annual rainfall induces a higher likelihood of using fertilizer and improved seed.

### 3.5.2 Results from the control function approach

*First stage results- Determinants of LGT market participation*

The results from the first stage of the control function approach are presented in Table 4. The second equation (column 2) includes Mundlak augmenting means as additional regressors; these results are interpreted. The results show that the instrumental variable, non-self-proportion of farmers selling to LGTs in the district, highly explains a farmer's sale to LGTs. Specifically, a one percentage point increase in the non-self-proportion of farmers selling to LGTs in a district increases a farmer's probability of selling to LGTs by 0.03.

Table 3-4 Drivers to LGT sales - First stage of the control function approach results

| | Equation 1 | Equation 2 |
|---|---|---|
| | LGT sales | LGT sales |
| Non-self-proportion of LGT sellers in district | 0.0357*** | 0.0347*** |
| | (0.00368) | (0.00374) |
| HH age | 0.00155 | -0.00316 |
| | (0.00370) | (0.00400) |
| HH gender | 0.0469 | 0.0490 |
| | (0.102) | (0.102) |
| HH education | 0.0334*** | 0.0136 |
| | (0.0103) | (0.0103) |
| Credit constrained | -0.127 | -0.259 |
| | (0.229) | (0.257) |
| Asset value ('00000Ksh) | -0.0296*** | -0.0336*** |
| | (0.00802) | (0.00772) |
| Own cultivated land (acres) | 0.0513*** | 0.0517*** |
| | (0.0106) | (0.0149) |
| AEZ controls | YES | YES |
| Year controls | YES | YES |
| Mundlak means | NO | YES |
| Constant | -4.884*** | -5.969*** |
| | (0.642) | (0.760) |
| N | 4,926 | 4,926 |

Robust standard errors in parentheses

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

Among other explanatory variables included in the model, area of own land cultivated highly explain sales to LGTs. An extra acre of owned cultivated land increases the probability of selling to LGTs by 0.05. This result highlights the self-selection issue in the type of farmers who sell to LGTs; farmers owning larger land areas for cultivation can take advantage of economies of scale to produce enough surplus and sell to LGTs, since these mostly buy in bulk.

*Determinants of improved seed and manure adoption*

Table 5 presents results on the estimation of the determinants of improved seed and manure adoption. After controlling for unobserved time-invariant variables in equation (2), sales to LGTs are shown to explain the adoption of improved seed at 95% confidence interval, but insignificant in explaining manure adoption. Past use of both SAIPs however highly explain current use of the same, pointing to the dynamism in SAIPs adoption and possibly reinforced by subsequent sales to LGTs as hypothesized. This result is similar to one obtained from the dynamic random effects Probit model.

Table 3-5 Drivers to improved seed and manure adoption

| | Equations 1 | | Equations 2 | |
|---|---|---|---|---|
| | Improved seed use | Manure (kg) | Improved seed use | Manure (kg) |
| Lagged dep. var | 1.302*** | 0.278*** | 1.246*** | 0.261*** |
| | (0.0936) | (0.0254) | (0.0969) | (0.0252) |
| LGT sales | 0.642*** | -184.5 | 0.451* | -338.1 |
| | (0.225) | (186.4) | (0.266) | (264.4) |
| Distance to | -0.00751 | -15.08 | -0.00715 | -11.41 |
| extension | (0.00607) | (11.78) | (0.00625) | (11.85) |
| HH age | -0.00518** | -5.224 | -0.00752*** | -10.22** |
| | (0.00259) | (4.570) | (0.00275) | (5.009) |
| HH gender | -0.257*** | -219.8** | -0.274*** | -235.4** |
| | (0.0769) | (94.67) | (0.0797) | (96.83) |
| HH education | 0.0178** | 29.28** | 0.00253 | -6.915 |
| | (0.00872) | (14.18) | (0.00889) | (15.09) |
| Credit constraint | -0.141 | -245.8 | -0.119 | -73.34 |
| | (0.149) | (320.5) | (0.189) | (349.6) |
| Asset value | 0.0168 | 41.77** | -0.0221* | -10.85 |
| (‘00000Ksh) | (0.0127) | (19.03) | (0.0117) | (21.27) |
| Own cultivated land | 0.0431*** | 42.62* | 0.00496 | 131.0*** |
| | (0.0140) | (23.81) | (0.0230) | (46.08) |
| Av. annual rainfall | 0.000257* | -1.523*** | 0.000455*** | -1.078*** |
| (mm) | (0.000133) | (0.249) | (0.000143) | (0.241) |
| Selection residual | 0.0599 | 437.9*** | 0.0283 | 319.9*** |
| | (0.0904) | (117.0) | (0.0985) | (121.1) |
| AEZ controls | YES | YES | YES | YES |
| Year controls | YES | YES | YES | YES |
| Mundlak means | NO | YES | NO | YES |
| Constant | -284.9*** | -184.5 | -312.5*** | 138,899** |
| | (50.46) | (186.4) | (54.69) | (69,772) |
| N | 3,047 | 1,896 | 3,047 | 1,896 |

Robust standard errors in parentheses

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

Other results from this analysis indicate that age of the household head is negatively correlated with both improved seed and manure use, with an extra year of age decreasing the amount of manure used by about 10kg and the probability of improved seed use by about 0.01. Similarly, being a female household head decreases the probability of using improved seed by 0.3, and the amount of manure used by over 235 kg. On the other hand, an increase in the size of own cultivated land by an acre increases the quantity of manure used by 131kg, while a millimeter (mm) increase in rainfall decreases this quantity by about a kilogram, perhaps signifying the inverse relationship between land productivity and soil fertility enhancing SAIPs. Conversely, the amount of annual rainfall is positively correlated with improved seed use.

*Determinants of fertilizer adoption*

As discussed in section 3, we apply the double hurdle model to analyze fertilizer demand. As before, the second equations control for unobserved variables through the inclusion of means of all the time-varying variables as additional regressors and are interpreted in this section. In the selection equation, the first selection equation (distance to extension) is negatively correlated to the decision to use fertilizer, implying that the further away a farmer is from extension advice, the lower the likelihood of adopting the input. The included lagged fertilizer use variable shows that past use of the SAIP highly informs adoption in subsequent years. Similarly, lagged fertilizer quantity positively affects current amount of fertilizer used.

Table 3-6 Drivers to fertilizer use – results from the Double Hurdle approach

| | Hurdle 1 | Hurdle 2 | Hurdle 1 | Hurdle 2 |
|---|---|---|---|---|
| | Probability of using fertilizer | Quantity of fertilizer demanded | Probability of using fertilizer | Quantity of fertilizer demanded |
| Distance to extension | -0.0343** | - | -0.0345** | - |
| | (0.0158) | | (0.0154) | |
| Group membership | -0.0624 | - | -0.0282 | - |
| | (0.210) | | (0.206) | |
| Lag. dependent variable | 2.895*** | 0.307*** | 2.900*** | 0.274*** |
| | (0.451) | (0.0168) | (0.444) | (0.0175) |
| LGT sales | 0.144 | 107.8*** | 0.153 | 112.5*** |
| | (0.396) | (22.17) | (0.382) | (25.98) |
| HH age | 0.00472 | 0.530 | 0.00487 | -0.0258 |
| | (0.00840) | (0.492) | (0.00809) | (0.492) |
| HH gender | -0.315 | -30.05* | -0.306 | -32.95** |
| | (0.227) | (15.84) | (0.220) | (15.57) |
| HH education | 0.0384 | 7.212*** | 0.0399 | 4.378*** |
| | (0.0279) | (1.410) | (0.0271) | (1.451) |
| Credit constraint | -0.631 | -65.01** | -0.722* | -41.27 |
| | (0.433) | (29.70) | (0.401) | (34.20) |
| Asset value (‘00000Ksh) | 0.0367 | 0.307 | 0.0219 | -4.454*** |
| | (0.0405) | (1.414) | (0.0345) | (1.667) |
| Own cultivated land | -0.0375 | 34.67*** | -0.0366 | 29.39*** |
| | (0.0241) | (1.799) | (0.0227) | (2.804) |
| Av. village Fertilizer | -0.0160 | -0.860 | -0.00936 | -1.819* |
| price (Ksh/kg) | (0.0176) | (0.973) | (0.0161) | (1.065) |
| Av. annual rainfall | 0.000772** | 0.171*** | 0.000864** | 0.0101 |

| | | | | |
|---|---|---|---|---|
| (mm) | (0.000383) | (0.0246) | (0.000372) | (0.0470) |
| Selection residual | 0.652*** | 12.63 | 0.574*** | 11.10 |
| | (0.247) | (11.07) | (0.219) | (11.31) |
| AEZ controls | YES | YES | YES | YES |
| Year controls | YES | YES | YES | YES |
| Mundlak means | NO | NO | YES | YES |
| Constant | -448.5* | -22,603* | -436.6* | -8,596 |
| | (253.6) | (13,092) | (259.8) | (14,813) |
| N | 2,757 | 2,757 | 2,757 | 2,757 |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results also show that sales to LGTs significantly affect the amount of fertilizer a household uses, but not the decision on whether to use fertilizer or not. This is a departure from earlier result obtained from the dynamic random effects Probit model which indicated sales to LGTs matter in the decision to participate in fertilizer market, and confirms the appropriateness of modelling fertilizer demand as a two-hurdle problem. Specifically, farmers who sell to LGTs on average use about 113kg of fertilizer more, compared to those that do not. Given that land size has been found to be positively correlated to fertilizer use, this high amount of fertilizer is not surprising. Selling to LGTs thus increases the rate of fertilizer used, through either of the channels discussed earlier; mitigation of market risks through forward contracts hence inducing more fertilizer use, offering higher output prices hence more incomes to buy more fertilizer, facilitating acquisition of inputs on credit, and information provision.

Sociodemographic variables important in explaining fertilizer demand include education and gender of the household head. An extra year of education of the household head increases the amount of fertilizer used by about 4kg, while being a female household head decreases this amount by about 33kg. On the other hand, being credit constrained decreases the likelihood of using fertilizer by 0.7, while an extra acre of own-cultivated land increase the quantity of fertilizer used by about 29kg. Ownership of huge tracts of cultivated land however lowers the likelihood of using fertilizer, perhaps due to economies of scale where use of intensification inputs may not be necessary to realize high outputs. Lastly, an increase in the average village fertilizer price decreases the quantity used of fertilizer used by about two kilograms.

### 3.6 Discussion and conclusions

The effect of farm productivity on commercialization is unequivocally established in the literature, and so is the effect of commercialization on welfare. Emerging literature assess the duality of the problem i.e. whether commercialization can induce farm productivity through incentivizing technology use and demand for extension. Most of this literature however is based on case studies of contractual arrangements between particular market actors and groups of farmers. This study extends this emerging literature by looking at how entry of large grain traders (LGTs) into smallholder farm markets may incentivize the use of sustainable agricultural intensification inputs (SAIPs) namely, inorganic fertilizer, improved seed, and organic manure.

The study uses a large dataset spanning a decade that permits the use of innovate methods to investigate the dynamic process of technology adoption, as well as, control for unobserved effects that confound most cross-sectional analyses. This not only allows us to interrogate the effect of past SAIPs adoption on current adoption behavior, but also the correlation between past and current sales to LGTs and SAIPs adoption. The study then uses a control function approach to investigate the effect of sales to LGTs on SAIPs adoption. The results show that sales to LGTs affect fertilizer demand but not that of improved seed or manure. This result is robust across all the analytical methods used in the study. Results from the dynamic random effects Probit model also show that use of improved seed and manure is persistent across years, unlike fertilizer whose past use does not affect current use.

The results imply the importance of the link between LGTs and SAIPs adoption (especially fertilizer) at the farm level. Given the critical role played by inorganic fertilizer in improving land productivity and the documented soil degradation in SSA, this linkage has important implications. Studies have already shown that farmers in the region are under-utilizing fertilizer (e.g. Sheahan et al., 2013). Policies that aim to strengthen and scale-out these LGTs-farmer engagements are desirable and should be pursued, as alternative interventions to enhance not only adoption but also the use rates of fertilizer.

Another important issue regards the factors identified in the study as key to explaining sales to LGTs, for example land ownership. Poorer farmers who face barriers in accessing these LGT markets may further be marginalized if these market actors crowd-out other smaller traders, who are the primary source of market for land-poor farmers. Strategies to improve the competitiveness of these smaller traders may thus be desirable in the short-run. On the production side, efforts to aggregate output from low-output producing farmers through formation of producer associations would mitigate the output barriers to accessing LGT markets, thus enabling the trickle down of the benefits of these engagements, even to land-poor farmers. LGTs may also be subsidized for their costs in engaging with lowly-producing farmers, in a Public-Private Partnership (PPP) type of approach.

## References


Abebe, G. K., Bijman, J., Kemp, R., Omta, O., & Tsegaye, A. (2013). Contract farming configuration: Smallholders' preferences for contract design attributes. *Food Policy*, *40*, 14–24. https://doi.org/10.1016/j.foodpol.2013.01.002

Asfaw, S., Pallante, G., & Palma, A. (2018). Diversification Strategies and Adaptation Deficit: Evidence from Rural Communities in Niger. *World Development*, *101*, 219–234. https://doi.org/10.1016/j.worlddev.2017.09.004

Bellemare, M. F. (2012). As You Sow, So Shall You Reap: The Welfare Impacts of Contract Farming. *World Development*, *40*(7), 1418–1434. https://doi.org/10.1016/j.worlddev.2011.12.008

Burke, W. J., Jayne, T. S., & Sitko, N. J. (2019). Do Medium-scale Farms Improve Market Access Conditions for Zambian Smallholders? *Journal of Agricultural Economics*. https://doi.org/10.1111/1477-9552.12360

Croppenstedt, A., Demeke, M., & Meschi, M. M. (2003). Technology adoption in the presence of constraints: The case of fertilizer demand in Ethiopia. *Review of Development Economics*, *7*(1), 58–70. https://doi.org/10.1111/1467-9361.00175

Engel, C., & Moffatt, P. G. (2014). Dhreg, xtdhreg, and bootdhreg: Commands to implement double-hurdle regression. *Stata Journal*, *14*(4), 778–797. https://doi.org/10.1177/1536867X1401400405

Ferris, S., Robbins, P., Best, R., Seville, D., Buxton, A., Shriver, J., & Wei, E. (2014). *Linking Smallholder Farmers to Markets and the Implications for Extention and Advisory Services. MEAS Discussion Paper Series*.

Govereh, J., & Jayne, T. S. (2003). Cash cropping and food crop productivity. *Agricultural Economics*, *28*, 39–50.

Grotti, R., & Cutuli, G. (2018). The Stata Journal. *Stata Journal*, *18*(4), 844–862. https://doi.org/The Stata Journal

Jin, S., & Jayne, T. S. (2013). Land Rental Markets in Kenya: Implications for Efficiency, Equity, Household Income, and Poverty. *Land Economics*, *89*(2), 246–271. https://doi.org/10.3368/le.89.2.246

Kihara, J., Nziguheba, G., Zingore, S., Coulibaly, A., Esilaba, A., Kabambe, V., … Huising, J. (2016). Understanding variability in crop response to fertilizer and amendments in sub-Saharan Africa. *Agriculture, Ecosystems and Environment*, *229*, 1–12. https://doi.org/10.1016/j.agee.2016.05.012

Maertens, M., & Vande Velde, K. (2017). Contract-farming in Staple Food Chains: The Case of Rice in Benin. *World Development*, *95*, 73–87. https://doi.org/10.1016/j.worlddev.2017.02.011

Manda, J., Alene, A. D., Gardebroek, C., Kassie, M., & Tembo, G. (2016). Adoption and Impacts of Sustainable Agricultural Practices on Maize Yields and Incomes: Evidence from Rural Zambia. *Journal of Agricultural Economics*, *67*(1), 130–153. https://doi.org/10.1111/1477-9552.12127

Marenya, P. P., & Barrett, C. B. (2009). Soil quality and fertilizer use rates among smallholder farmers in western Kenya. *Agricultural Economics*, *40*(5), 561–572. https://doi.org/10.1111/j.1574-0862.2009.00398.x

Minten. (2010). Agricultural extension and imperfect supervision in contract farming: evidence from Madagascar. *Agricultural Economics*, (0), 1–33. Retrieved from http://onlinelibrary.wiley.com/doi/10.1111/j.1574-0862.2010.00462.x/full

Muyanga, M., Jayne, T. S., & Burke, W. J. (2013). Pathways into and out of Poverty: A Study of Rural Household Wealth Dynamics in Kenya. *Journal of Development Studies*, *49*(10), 1358–1374. https://doi.org/10.1080/00220388.2013.812197

Olwande, J., Smale, M., Mathenge, M. K., Place, F., & Mithöfer, D. (2015). Agricultural marketing by smallholders in Kenya: A comparison of maize, kale and dairy. *Food Policy*, *52*, 22–32. https://doi.org/10.1016/j.foodpol.2015.02.002

Pretty, J., & Bharucha, Z. P. (2014). Sustainable intensification in agricultural systems. *Annals of Botany*, *114*(8), 1571–1596. https://doi.org/10.1093/aob/mcu205

Pretty, J., Toulmin, C., & Williams, S. (2011). Sustainable intensification in African agriculture. *International Journal of Agricultural Sustainability*, *9*(1), 5–24. https://doi.org/10.3763/ijas.2010.0583

Rabe-Hesketh, S., & Skrondal, A. (2013). Avoiding biased versions of Wooldridge’s simple solution to the initial conditions problem. *Economics Letters*, *120*(2), 346–349. https://doi.org/10.1016/j.econlet.2013.05.009

Ricker-Gilbert, J., Jayne, T. S., & Chirwa, E. (2011). Subsidies and crowding out: A double-hurdle model of fertilizer demand in Malawi. *American Journal of Agricultural Economics*, *93*(1), 26–42. https://doi.org/10.1093/ajae/aaq122

Sheahan, M., Black, R., & Jayne, T. S. (2013a). Are Kenyan farmers under-utilizing fertilizer ? Implications for input intensification strategies and research. *JOURNAL OF FOOD POLICY*, *41*, 39–52. https://doi.org/10.1016/j.foodpol.2013.04.008

Sheahan, M., Black, R., & Jayne, T. S. (2013b). Are Kenyan farmers under-utilizing fertilizer? Implications for input intensification strategies and research. *Food Policy*, *41*, 39–52. https://doi.org/10.1016/j.foodpol.2013.04.008

Sitko, N. J., & Chisanga, B. (2016). *How Is Multinational Investment in Grain and Oilseed Trading Reshaping the Smallholder Markets in Zambia?* (February).

Sitko, N. J., & Jayne, T. S. (2014). Exploitative Briefcase Businessmen, Parasites, and Other Myths and Legends: Assembly Traders and the Performance of Maize Markets in Eastern and Southern Africa. *World Development*, *54*, 56–67. https://doi.org/10.1016/j.worlddev.2013.07.008

Sitko, N. J., Jayne, T. S., Burke, W. J., & Muyanga, M. (2017). Food System transformation and Market

Evolutions: an analysis of the rise of large-scale grain trading in Sub-Saharan Africa. In *International Development Working Paper (forthcoming). Michigan State University*. https://doi.org/10.13140/RG.2.2.18589.10725

Ton, G., Vellema, W., Desiere, S., Weituschat, S., & D'Haese, M. (2018). Contract farming for improving smallholder incomes: What can we learn from effectiveness studies? *World Development*, *104*, 46–64. https://doi.org/10.1016/j.worlddev.2017.11.015

Wooldridge, J. M. (2002). Econometric Analysis of Cross Section and Panel Data. *MIT Press: Cambridge, MA, USA*. https://doi.org/10.1515/humr.2003.021

Wooldridge, J. M. (2005). Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of Applied Econometrics*, *20*(1), 39–54. https://doi.org/10.1002/jae.770

Chapter 4

# 4 Weather Uncertainty and Demand for Information in Agricultural Technology Adoption; Case of Namibia

**Abstract**

Climate change has compounded the uncertainties inherent in agriculture. Farmers have to make decisions faced with increasingly fluctuating weather, leaving them vulnerable. Access to climate-related information in developing countries, incidentally also the hardest hit by adverse effects of climate change, is very limited. Given a choice set of technologies that yield different payoffs depending on seasonal weather outcomes, ambiguity arising from imprecise weather information may lead to sub-optimal choices. Using data from a framed experiment carried out with 300 farmers in northern Namibia, this study investigates how uncertainty about the weather affects farmers' decision making. To establish the demand for weather information, the study elicits farmers' willingness to pay for information at different levels of uncertainty. The experiment results show that high levels of weather uncertainty, in addition to subjective ambiguity aversion, dampen technology uptake. There is also a high demand for weather information that reduces this uncertainty, regardless of individual attitudes towards uncertainty. The results also show that access to weather information enables farmers to make welfare improving choices given a set of farming technologies. These results highlight the importance of investing in the provision of weather information to farmers as a means of enhancing take-up of technology that creates resilience in agricultural production, in the face of the changing climate.

## 4.1 Introduction

More than before, decision makers in the agricultural sector have to contend with an increasingly uncertain environment due to effects of climate change. Access to timely weather-related information can help these farmers prepare through adaptive or coping strategies to dampen the negative effects of climate change (Singh et al. 2017; Di Falco, Veronesi, and Yesuf 2011). While sub-Saharan Africa (SSA) has been projected as the region to be most affected by the negative effects of climate change (Pretty et al. 2011), it is also the region where availability and access to climate-related information is weakest (Mason et al., 2015).

The slow rate of technical change in developing countries has been blamed on low rates of diffusion of new technology to targeted populations. For the most part, development economists have attributed this problem to institutional barriers to adoption. Fairly recent literature describes poor farmers as caught in poverty traps due to underlying liquidity constraints and aversion to uncertain technologies, creating an inertia in the take-up of risky but high-yielding production technologies (Brick and Visser, 2015; Cole et al., 2013; Giné and Yang, 2009). Most literature on time preference also shows poor farmers to exhibit high discount rates, thus failing to invest in projects with no immediate returns (an exception is a recent study by Liebenehm and Waibel (2014) that surprisingly shows wealthier farmers to be more impatient). This has brought to the fore behavioural attitudes as key drivers in the technology diffusion and rural development literature (Feder and Umali, 1993).

While extant literature has explored how aversion to uncertainty affects agricultural technology uptake (Elabed and Carter 2015; Alpizar et al., 2011; Akay et al. 2012; Takahashi 2013), there is a dearth of evidence on how reducing this uncertainty improves technology adoption decisions. This is an important aspect in the fight against climate change since it gives prominence to the role of weather information provision in the adoption of stress-adapted technologies. To fill this gap in the literature, our study utilizes both survey data and a framed experiment to assess how providing weather information improves adoption decisions for improved agricultural technologies among smallholder farmers.

Further, the study elicits the willingness to pay (WTP) for such information at various levels of uncertainty, to establish its demand. While most weather information is publicly provided, studies show that this information is usually unreliable due to short lead time, frequency and accuracy (Tall, Coulibaly, and Diop 2018; Njau 2010). Eliciting demand for weather information among farmers could thus point to the potential for the entry of private weather information providers.

## 4.2 Choice under imprecise information

Ellsberg's (1961) seminal work revived the problem of “Knightian uncertainty” in decision theory, whereby decision makers are faced with imprecise information on the likelihood of an event happening. This has seen an upsurge of research interest on imprecise information in decision making, both in theoretical and applied economics work. An unequivocal consensus as evidenced by studies shows that aversion to uncertainty affects decision making. For example, Yates and Zukowski (1976) found that subjects were willing to bet more on a bag where the precise number of blue and red chips was known compared to one where they did not have information on the proportion of chips in the bag.

Most of these studies assume decision making under complete uncertainty (where probability distributions are completely unknown). In most life decisions, however, decision makers have some information regarding the distribution of the likelihood of an event happening. This is exemplified in seasonal weather information, for example, which is the subject of interest in this article; farmers have some priors based on their farming experience and peer networks. One of the relevant early studies to investigate choice behaviour when a decision maker has formed some priors is Becker and Brownson (1964), who define ambiguity as any distribution of probabilities other than a point estimate.

Other recent literature on uncertainty with priors includes Gilboa and Schmeidler (1989), who posit that, given too little information in a bet to form a prior, the decision maker takes the minimum expected utility (MEU) over all priors in a probability set to evaluate the bet. Ghirardato et al. (2004) generalized the MEU model to allow decision makers to assign different weights on the minimum and maximum expected utility leading to the α-MEU model. Of interest is whether the effects of a decision maker’s (DM’s) “revealed” ambiguity on a dependent variable can be separated into its components: individual attitude towards ambiguity and the range of ambiguity itself. From these studies, it is not clear whether exhibiting a large aversion to ambiguity is due to the DM being more pessimistic (subjective) or due to the information being more imprecise (objective) (Hayashi and Wada, 2010). Klibanoff et al. (2005) explores what happens if a DM’s ambiguity aversion is decreased while holding the priors and risk attitude constant or, conversely, what happens if the perceived priors change, holding ambiguity and risk attitudes constant. In their experiment, Hayashi and Wada (2010) controlled for the objective part (set of priors) and attempted to elicit the subjective part (ambiguity aversion).

Guided by the above premise of the separate effects of the subjective and objective sources of observed ambiguity, this study aims to look at the separate effects of subjective ambiguity aversion and objective uncertainty aversion on technology choice. To our knowledge, this is the first study to investigate this in the agricultural setting. Close studies include Tonsor (2018), who has looked at how uncertainty and reference point (best outcome experienced before) shape decision making among cattle producers in the United States.

Likewise, other similar studies have for the most part only looked into the subjective part of ambiguity aversion. For example, Cardenas and Carpenter (2013) found that ambiguity aversion was negatively correlated with well-being measures among participants drawn from Latin America. On climate change, Alpízar et al. (2011) focus on adaptation and show that ambiguity-averse farmers are more likely to take up adaptation measures in the face of climate change. Andrews et al. (2018), on the other hand, focus on mitigation and show experimentally that individuals invest in high-risk, high-reward mitigation technologies, thus exhibiting risk-seeking behaviour, when the stakes are high and certain but low-rewarding options are not sufficient to mitigate emissions.

Working on index-based insurance, Elabed and Carter (2015) focus on whether farmers exhibit aversion to compound risk and how this affects take-up of agricultural index-based insurance. Mcintosh et al. (2015), on the other hand, elicit coffee farmers' WTP for index-based insurance under varying degrees of rainfall and basis risk and compare this with a predicted optimal WTP given the expected utility with and without insurance, thereby exploring behavioural responses to probabilistic insurance. Our elicitation of subjects' WTP for uncertainty-reducing information (weather information) is similar in approach to Mcintosh et al. (2015), but our focus is on demand for weather information under various uncertainty levels, a novel contribution in the agricultural technology adoption literature.

Investigating farmers' choices under different uncertainty levels given their subjective attitudes towards uncertainty is an important aspect in the intervention space, especially relating to information provision. The implications of the study are of significance due to the rising uncertainty in farming environments driven by increasing climate variability. Predicting weather outcomes is now harder even among experienced farmers, and providing weather (climate) information could assist in stabilizing outcomes and sustaining livelihoods.

## 4.3 Study area and weather information use

The Namibian climate is characterized by sparse and erratic rainfall, with 92% of the land area defined as hyper-arid, arid or semi-arid (Tadross and Johnston, 2012). Most of the rain in the country is received in the northern part, which also has the highest population (Mendelsohn et al., 2002). Climate change is already affecting the fragile systems therein and projected impacts are grave unless urgent adaptive measures are taken (Reid et al., 2007). UNDP (2015) puts Namibia as the seventh most at-risk country in terms of climate change-related agricultural losses.

In the survey conducted in conjunction with this experiment, 52% responded that they receive information on weather regarding the management of their crops, while about 45% responded likewise regarding livestock management (See Figure 1). In an attempt to see if there is demand for climate information among non-recipients, we asked the remaining 48% and 55% that do not receive climate information on crop and livestock management respectively how they would use this information if they received it.

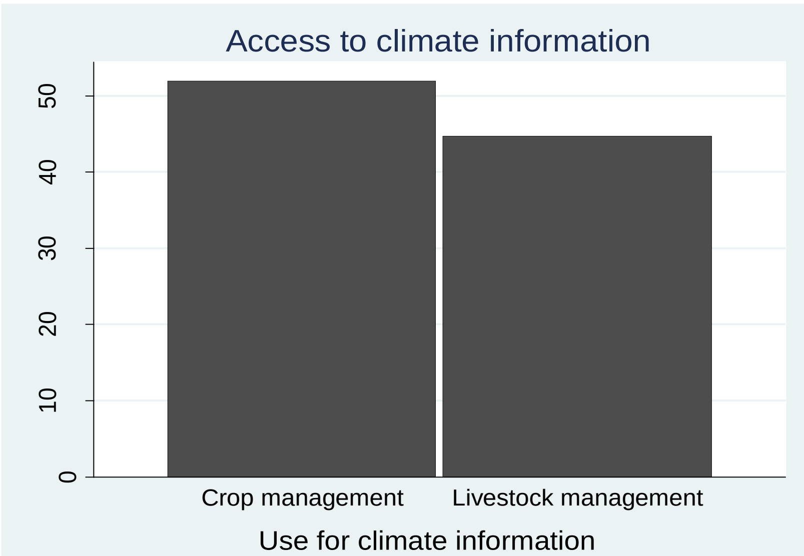


*Figure 4-1 Access to climate information for crop and livestock management*

For crop management, a majority indicated they would change timing of activities, e.g., planting time (36%), while 28% indicated they would change crops and/or crop varieties that they planted, and a further 34% said they would change their grain storage (See Figure 2a).

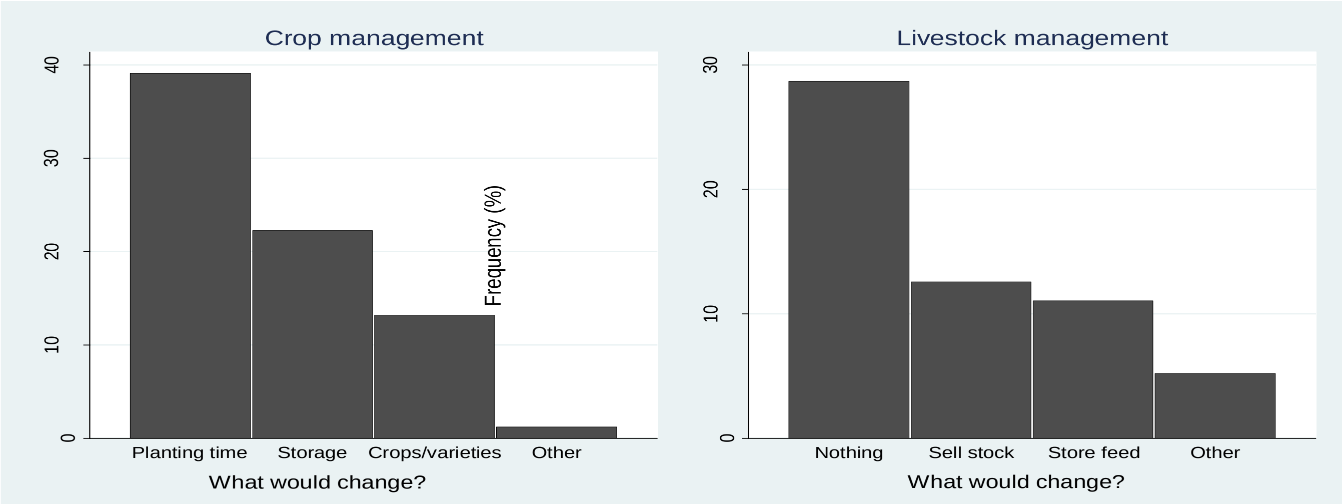


*Figure 4-2 Potential uses for climate information among non-recipients*

On the other hand, of those who did not receive climate information on livestock management, a majority indicated they might not use such information even if it was available to them (29%), a clear indication of the lack of awareness of strategies to mitigate against livestock losses in case of climate stressors like drought. However, 23% indicated they would use the information to manage stock size through selling and a further 25% felt that getting climate information might enable them to store livestock feed better (see Figure 2b).

### 4.4 Sample selection

Selection of the sample followed two procedures: first, selecting respondents for the survey and second, selecting participants for the experiment. To achieve the first, a multistage sampling procedure was used to select 600 households from three regions in northern Namibia. In the first step, the three regions (Oshana, Omusati and Oshikoto) were purposively selected based on agricultural productivity and exposure to climate change. In the next step, one constituency was selected from Oshana, one from Oshikoto, and three from Omusati, representing the diversity within the regions. Random proportionate to size sampling was then employed to determine the number of villages from each constituency to include in the sample, with 10 households from each village being randomly selected for the study.

In the second process, a criterion of basic literacy was set to select who among the survey respondents would be included in the experiment. Qualifying participants had a minimum education level of grade three and could read and write in the local language (*Oshiwambo*). Given the low qualification criteria, many respondents in the survey qualified (an average of seven out of ten per village). However, logistical challenges, where the experiment team had to cover two villages (sessions) per day, meant that not all qualifying respondents from each village could be included, since some arrived late. Thus, at the end of the exercise, only half of the surveyed respondents participated in the experiment (see Table 1).

Table 4-1 Participant Characteristics (n=300)

| Variable | Omusati | Oshana | Oshikoto | Overall |
|---|---|---|---|---|
| Gender (% female) | 78 | 71 | 67 | 72 |
| Age (years) | 49.4 (16.6) | 48.3 (18.4) | 51.3 (15.8) | 49.7 (16.9) |
| Education level (grade) | 7.8 (3.2) | 7.4 (3.5) | 7.0 (3.5) | 7.5 (3.6) |

A high proportion of households in the study region are female-headed, as reflected in the sample. Mean education level was high, with the median participant having attained grade 7, though the dispersion around the mean is large given that the lowest level attained was grade three. While this may appear to show high education levels in the region, one must take into account that the participants were selected conditional on having gone to school. This is not unique in experimental studies where participants need to have some basic literacy level.

### 4.5 An overview of experimental tasks completed

There were five series of games to play in an experiment session (see Table 2). First, participants completed a simple risk experiment aimed at eliciting risk preferences (series 1), then moved on to a framed experiment involving choices of different technologies to use for farming in a typical season under varying chances of good weather. The framed experiment had four series of games (series 2 to 5). In series 2, the chances (probabilities) of good weather were disclosed to the participants before playing the games, while in series 3 the participants were only told the range of chances (probability set) within which good weather was likely to occur in the season.

Table 4-2 Overview of Games Played in the Experiment

| **Series 1** Simple risk preferences elicitation at [..] probability (set) of good outcome | **Series 2** Technology choice under risk at [..] probability of good weather | **Series 3** Technology choice under uncertainty at [..] probability set of good weather | **Series 4** WTP for information at [..] probability set of good weather | **Series 5** Technology choice with/out information at [..] probability set of good weather |
|---|---|---|---|---|
| 50% | 30% | 0-100% | 0-100% | 0-100% |
| 0-100% | 50% | 20%-40% | 20%-40% | 20%-40% |
| | 70% | 10%-50% | 10%-50% | 10%-50% |
| | | 60%-80% | 60%-80% | 60%-80% |
| | | 50%-90% | 50%-90% | 50%-90% |

After completing series 3 games, where the chances of good weather in the season were uncertain, participants played information games (series 4), where they had an opportunity to purchase information on the precise probability of good weather. In the fifth and final series (series 5), participants played series 3 games again, but this time some had information on the precise probability of good weather (those who purchased information in series 4) and others knew only the range within which the chance of good weather was likely to occur (those who did not purchase information).

## 4.6 Experiment design

This section presents designs of the risk preference elicitation methods, the framed experiment, and the elicitation of the willingness to pay for weather information.

### 4.6.1 Choice under risk and uncertainty

A pre-test was conducted in the study area (in a region outside the sample) prior to collecting the data. This revealed that a detailed risk and ambiguity aversion elicitation method (e.g. the commonly used multiple price list) fatigued the participants before they got to play the framed experiment games. A simpler version similar to the one by Eckel and Grossman (2002) was therefore adopted (see Table 3).

Table 4-3 Risk Preferences Elicitation

| Gamble | Payoffs | | ✓ |
|---|---|---|---|
| | Low outcome | High outcome | |
| 1 | 24 | 24 | |
| 2 | 18 | 36 | |
| 3 | 12 | 48 | |
| 4 | 6 | 60 | |
| 5 | 0 | 72 | |

Participants were presented with five gambles, each with two possible outcomes. The probability of occurrence for the high outcome was set at 50% for the risk game and completely unknown for the ambiguity game.

*Risk aversion measure*

We let the number of the gamble be an index measure of the underlying continuous risk level. From the framing, an extremely risk-averse individual would sacrifice expected payoffs for certainty, thus opting for *gamble 1*, while moderately risk-averse participants would go for *gambles 3* or *4*. Conversely, risk-neutral participants would go for the maximum expected payoff, preferring *gamble 5*. Risk-seeking participants would also opt for a higher-risk option even if it involves the same or lower expected payoff and thus would choose *gamble 5* (Eckel and Grossman, 2002).

*Ambiguity aversion measure*

Following Klibanoff et al. (2005) and Cardenas and Carpenter (2013), we define ambiguity aversion with reference to a participant's risk aversion. In this regard, we use the standard deviations of the choices (high and low outcomes) so as to create a continuous measure, rather than use the discrete choices themselves. Ambiguity aversion is thus measured as the difference in the standard deviation of choice under risk and that under ambiguity. The constructed measure is therefore decreasing in ambiguity aversion; the lower the measure, the higher the degree of ambiguity aversion. Results show that the sample distribution of the measure is almost symmetrical with a mean of -0.47, implying a slightly higher proportion of the sample is ambiguity averse (see Figure 3).

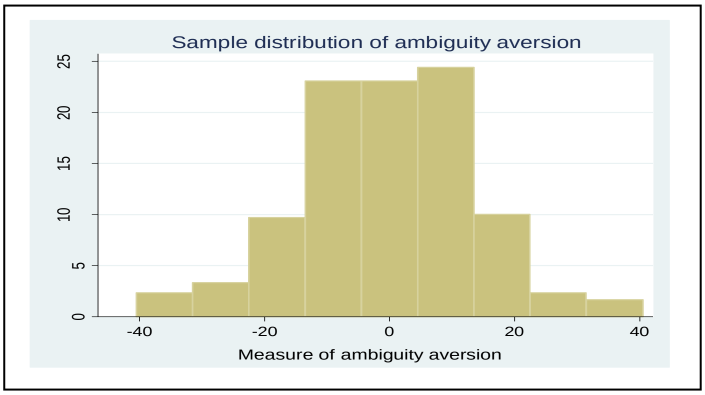


*Figure 4-3 Sample distribution of ambiguity aversion measure*

Following Cardenas and Carpenter (2013), we also allow for a spline specification where the ambiguity aversion measure is split into those who are strictly ambiguity averse (negative values of the ambiguity aversion measure) and those who seek more risk under ambiguity (positive values of the ambiguity aversion measure). This allows for a kink in the relationship between ambiguity aversion and the dependent variables discussed in the following sections, i.e.,

$$y_i = \beta_{0i} + \beta_{1i}(ambiguity_i - risk_i) + \beta_{2i} \max\{ambiguity_i - risk_i, 0\} + \theta \boldsymbol{X}_i + \boldsymbol{\varepsilon_i}$$

where $y_i$ is the dependent variable of interest (e.g., choice of technology), $\boldsymbol{X}_i$ is a vector of controls and $\boldsymbol{\varepsilon_i}$ is an error term; and '$ambiguity_i - risk_i$' is a measure of a participant's reaction to uncertainty as explained above. The spline specification allows for the more ambiguity-averse (negative measure) participants to have different outcomes from the ones who seek more risk under ambiguity (positive measure).

### 4.6.2 Technology choice: A framed experiment

The experiment adopts a within-subjects design to test how uncertainty shapes decisions over three technology choices. In the framing, a participant chooses a technology to use in a typical farming season from among three options: an off-farm work option, a seed technology adapted to climate stressors such as drought ('adaptive seeds'), and an improved seed technology (hybrid seed) (see Table 4). The off-farm work option has a constant payoff of N$75 in both good and bad weather outcomes and is analogous to the sure bet option in standard risk-aversion elicitation methods. The second option is that of an adaptive seed technology that is resilient even in bad weather, giving a net payoff of N$25 and a high of N$150 in good weather. The last option of improved seed technology has the highest payoff in good weather (N$225) but gives a negative payoff (-N$25) in bad weather. The negative payoff indicates that the farmer incurs costs, yet gets very low or zero returns in bad weather, thus incurring losses.

In similar studies (Brick and Visser, 2015; Jumare et al., 2018) , 'traditional seed' is used in lieu of the 'off-farm work' option to represent resilience of landraces in bad weather. In our study area, this might be true in the case of sporadic rainfall but is unrealistic in the case of droughts, which are growing in frequency and which lead to crop failure even for the traditional seeds. There exist several government and non-government organizations (NGO) funded programs in the study area; hence, the adoption of this framing is salient for the participants. Drought-resistant and hybrid seed varieties exist in the area too; hence, they are familiar concepts to the participants. The framing for the payoffs for each of these technologies, while not the same as in reality, reflects the payoff of each technology relative to the other. For example, while improved seeds do well in good weather compared to adaptive seeds, the latter do better in bad weather. One is also paid if working off-farm, whether the weather for that season is bad or good.

Table 4-4 Risk and Uncertainty Games

| Choice | Weather outcome | | Expected payoffs given probability (set) | | |
|---|---|---|---|---|---|
| | Good | Bad | 50%; 0-100% | 30%; 20%-40%; 10%-50% | 70%; 60%-80%; 50%-90% |
| Off-farm work | 75 | 75 | 75.0 | 75.0 | 75.0 |
| Adaptive seeds | 150 | 25 | 87.5 | 62.5 | 112.5 |
| Improved seeds | 225 | -25 | 100.0 | 50.0 | 150.0 |

Given the potential loss in the third option under the bad weather outcome, we made sure the initial endowment given to participants to incentivize the games was enough to cover this. We also varied the amount given to participants in different sessions (N$30 and N$60) to control for the effect of initial wealth on decisions made in the experiment. To control for order effects, games in each of the series (risk or uncertainty games) were randomized but participants always completed the risk games first before proceeding to the uncertainty games, in order to increase salience.

### 4.6.3 Willingness to pay for weather information

After playing the third series of the games (uncertainty games), we introduced the possibility of reducing this uncertainty by receiving information on the precise probability of good weather in the season. Participants were given the opportunity to purchase this information before playing the uncertainty games again. The Becker, Degroot and Marschak (1964) (hereafter BDM) method was used to incentivize the payments and elicit true WTP for the uncertainty-reducing information (weather information). Participants first stated their WTP, then a random price was drawn. If the stated WTP was equal to or above the drawn price, the participant received information; if it was lower, the participant was not given information. This was done for all the five uncertainty ranges represented by the different probability sets of good weather (the fourth series of the games). All participants played the uncertainty games a second time (the fifth and last series of the games) either with or without information on precise probabilities of good weather as determined using the BDM method explained above.

Most of the climate- (weather) related information in developing countries is provided for free, either by government agencies or development aid organizations. Thus there is little cost information on which to base our bidding prices. Ultimately, a price range of 0 - N$25 was chosen based on participants' ability to pay using the initial endowments given and expected payoffs. A zero-information cost was included to capture the non-willingness to pay for some probability sets and is in congruence with the actual situation on the ground where information is given out for free.

## 4.7 Experiment procedures

As mentioned in the preceding section, the experiment adopted a within-subject design where participants completed all the games in the five series (see Table 2), i.e., two games in *series 1*; three games in series *2*; and five games each in series *3, 4* and *5.* Given the low literacy levels of the participants, a key concern was to make sure that the length of the experiment did not compromise data quality due to fatigue. Each session was thus split into two, where *series 1* to *3* games were played first before a half-hour refreshment break, then the rest of the games completed. The games were also made as easy as possible to understand, using visual aids as explained further in this section.

At the beginning of the experiment session, participants were given cards as they entered the venue, indicating the experiment number and showing them where to sit. The games were then explained, including how winning (and losing) would occur in the games. Participants were told that they had been allocated money for showing up, which they could use to pay for any losses in the games, as well as use to buy information in the WTP games. The remaining amount plus any winnings in the games would be handed out at the end of the sessions. This point was reiterated several times during the course of the games especially where it involved incurring losses and in the payment for information games. To disentangle the wealth effect on decisions made in the games, the initial endowment was varied at N$30 (low) and N$60 (high) and randomly assigned in sessions. This does not seem to have had any effect on choice behaviour, based on the results presented later in the results section.

The study utilized big posters translated to the local language, Oshiwambo, to represent the games. To explain concepts such as probability, white and black balls were used, where the black balls represented the probability of good weather. To explain a 30% probability of good weather, for instance, three black and seven white balls were put in an opaque bag and participants were told that if a black ball was drawn, the weather for that game (season) was good. Practice rounds were played to demonstrate this. Similarly, in the uncertainty rounds, participants were told that the bag could contain a range of a number of black or white balls depending on the particular probability set of good weather under consideration. In the 20%-40% probability set, for instance, the bag could contain two black and eight white balls, or three black and seven white balls, or four black and six white balls. This was demonstrated in examples, and the big posters representing the game also had these different variations of possible bag compositions drawn on the side.

In the WTP for weather information games (*series 4*), after the participants in a session had finished indicating how much they were willing to pay for information in a particular probability set, one of them volunteered to draw a card from a stack labelled 0 to 25. The drawn number represented the actual cost of the information and participants with equal or above stated WTP qualified to receive information for that particular game.

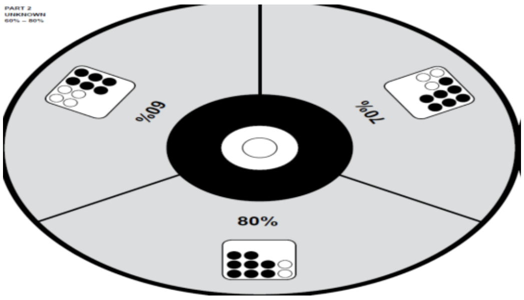


*Figure 4-4 Spinning wheel to determine precise probabilities (60%-80% uncertainty range)*

Next, a wheel with the appropriate number of ball variants for the specific probability set (e.g., the example in Figure 4) was spun to determine the precise probability of good weather. This was done discreetly and the information revealed to only the participants who qualified to receive information.

## 4.8 Results and discussion

Results from the experiments and a discussion of these findings are presented next.

### 4.8.1 Risk and ambiguity aversion measures

Consistent with similar field experiment studies (Brick and Visser, 2015; Cardenas and Carpenter, 2013), the results of the baseline risk gamble show prevalent risk aversion in the sample with a mean choice of 2.94, which is closest to lottery gamble 3 (see Table 5).

Table 4-5 Risk and Ambiguity Preferences (n=300)

| Gamble | Payoff | | Expected payoff (50% prob.) | Risk (standard deviation of payoff) | Frequency (%) | |
|---|---|---|---|---|---|---|
| | Low | High | | | Risk choice | Ambiguous choice |
| 1 | 24 | 24 | 24 | 0 | 13.24 | 15.33 |
| 2 | 18 | 36 | 27 | 9 | 23.69 | 22.30 |
| 3 | 12 | 48 | 30 | 18 | 31.36 | 31.01 |
| 4 | 6 | 60 | 33 | 27 | 19.51 | 21.25 |
| 5 | 0 | 72 | 36 | 36 | 12.20 | 10.10 |
| **Mean gamble** | | | | | **2.94 (0.071)** | **2.89 (0.071)** |

The distribution in the complete uncertainty framing is similar to the risk framing but shifts slightly to the left to represent more conservative choices under ambiguity, as seen in Figure 3 earlier in this article. For example, more participants chose the ‘safe’ gamble (gamble 1) under uncertainty (15%) than under risk (13%). Likewise, more chose the riskiest option (gamble 5) under risk (12%) than under uncertainty (10%). The mean choice of 2.89, however, is most similar to the one under risk and corresponds to gamble 3.

### 4.8.2 Technology choice under risk and uncertainty

Next we investigate how participants' attitudes towards risk and uncertainty affect technology choice. As expected, the mean choice of technology was highest at 70% and lowest at 30% probabilities of good weather (see Figure 5a). Because our choice variable is increasing in riskiness and expected payoffs (0=Off-farm work; 1=Adaptive seed; 2=Improved seed), this implies that with a higher probability of good weather, participants opted for riskier technologies associated with higher expected payoffs, relative to the safe but low return option (off-farm work). The opposite applies for low probability of good weather (30%). At a 50% probability of good weather, the mean choice corresponds to the adaptive seed option, indicating the trade-off of high expected payoffs in the improved seed option for low variance in yields associated with the adaptive seed option.

Under uncertainty, the mean choice was highest at the 60%-80% probability sets and lowest at the 20%-40% probability sets (see Figure 5b). Observed mean choice at complete uncertainty (0-100% probability set) is about the same as that at the 50% risk level, corresponding to the adaptive seed option. Given the wide range of uncertainty, participants seem to choose a low variance technology to "hedge" against risk, while still getting a better expected payoff than the baseline option (off-farm work). This zero-variance, low expected payoff option is mostly chosen for the low probability sets (20%-40% and 10%-50%), as the low mean choices for these probability sets reveal.

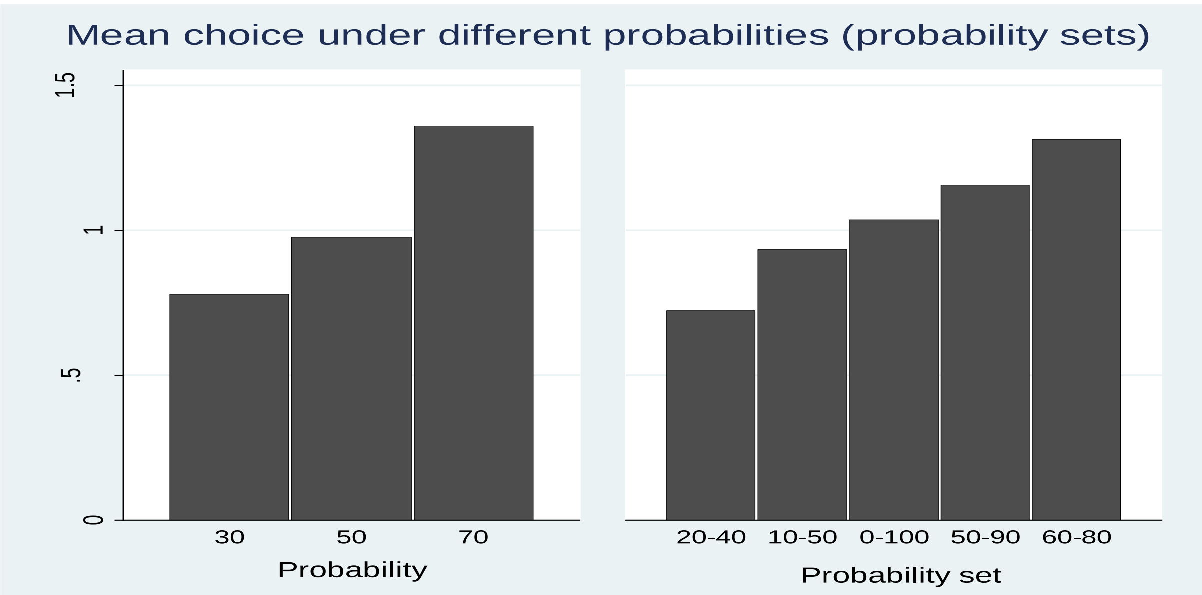


*Figure 4-5 Technology choice under risk and uncertainty*

On the other hand, participants go for riskier, higher-yielding technologies in probability sets with higher probabilities of good weather (50%-90% and 60%-80%). Non-parametric tests using a Wilcoxon sign-rank test show that these differences in choices are significant (see Table 6).

Table 4-6 Difference in Choices under Different Probabilities (Probability Sets) of Good Weather

| Probability (set) % | Probability (set) % | z | Prob > \|z\| |
|---|---|---|---|
| ***Risk choices*** | | | |
| 30 | 50 | -3.595 | 0.0003 |
| 30 | 70 | -7.909 | 0.0000 |
| 50 | 70 | -7.445 | 0.0000 |
| ***Uncertainty choices*** | | | |
| 20-40 | 10-50 | -3.579 | 0.0003 |
| 20-40 | 60-80 | -8.081 | 0.0000 |
| 20-40 | 50-90 | -6.183 | 0.0000 |
| 20-40 | 0-100 | -4.845 | 0.0000 |
| 10-50 | 60-80 | -5.381 | 0.0000 |
| 10-50 | 50-90 | -3.372 | 0.0007 |
| 10-50 | 0-100 | -1.928 | 0.0539 |
| 60-80 | 50-90 | 3.123 | 0.0018 |
| 60-80 | 0-100 | 4.414 | 0.0000 |
| 50-90 | 0-100 | 2.110 | 0.0349 |

Higher preference for riskier technologies at 60%-80% probability than at 50%-90% probability could imply that participants over-weight the lowest probability in the set, thus choosing more conservatively at 50%-90%, in line with the MEU theory discussed before. The reverse happens for lower probability possibility sets, however, where more participants choose the safe option at 20%-40% probability than at 10%-50% probability. It would thus seem that for low probability sets, the highest possible probability in the set, rather than the lowest, biases the choice. The choice under the 0-100% probability set seems to confirm this, as riskier choices are made in this set compared to 10%-50% and 20%-40%, even though the least possible probability in this set is zero.

*Risk aversion and technology choice*

To build up the analysis, we first look at the effect of risk aversion on choice under the risk scenarios (30%, 50% and 70%). In the analysis, we control for socio-demographic and household characteristics of the participant, such as education, age, gender and household income. We also control for the initial wealth given to each participant at the start of the experiments. The results in Table 7 are from an Ordinal Logit model and are displayed as proportional odd ratios; the risk-aversion measure is standardized to one standard deviation and zero mean.

Risk aversion significantly affects choice of technology at 50% and 70% probability of good weather; as risk aversion increases, participants are more likely to opt into the off-farm work ("safe") option relative to adaptive and improved seed options. Specifically, for a one standard deviation increase in risk-aversion attitude, the odds of opting into off-farm work relative to the adaptive and improved seed options are 1.28 and 1.36 times greater at the 50% and 70% probabilities of good weather outcome, respectively.

Pooling across the risk levels enables us to look at the effect of the probability levels of good weather in addition to the effect of risk aversion. As expected, results show that as the probability increases from 30% (baseline) to 50% and 70%, the odds of opting into on-farm activity (adaptive and improved seed options combined) relative to off-farm work increases. Specifically, for an increase in the probability of a good weather outcome from 30% to 50%, the combined odds of opting into adaptive and improved seed options relative to off-farm work are 1.6 times greater. These odds are even greater (4.8 times) for an increase in the probability of good weather from 30% to 70%.

Risk aversion in the pooled regression still affects technology choice in the same direction as in the individual probability levels. For a one standard deviation increase in risk-aversion attitude, the odds of opting into off-farm work relative to the combined options of adaptive and improved seeds are 1.14 times greater.

Table 4-7 Technology Choice under Risk

| VARIABLES | (1)<br>**30%** | (2)<br>**50%** | (3)<br>**70%** | (4)<br>**Pooled** |
|---|---|---|---|---|
| Risk aversion | 0.886 | 1.280** | 1.363*** | 1.142* |
| | (0.102) | (0.152) | (0.162) | (0.0864) |
| Initial wealth | 0.991 | 1.137 | 1.122 | 1.077 |
| | (0.141) | (0.167) | (0.166) | (0.102) |
| Gender | 1.030 | 0.860 | 0.678 | 0.843 |
| | (0.268) | (0.230) | (0.186) | (0.146) |
| Age | 1.001 | 1.007 | 1.006 | 1.004 |
| | (0.00807) | (0.00794) | (0.00833) | (0.00522) |
| Occupation | 0.996 | 1.000 | 1.007 | 1.002 |
| | (0.0208) | (0.0214) | (0.0220) | (0.0140) |
| Education | 0.934* | 1.026 | 1.072* | 1.007 |
| | (0.0372) | (0.0411) | (0.0443) | (0.0264) |
| Household size | 0.973 | 0.983 | 1.000 | 0.981 |
| | (0.0379) | (0.0380) | (0.0401) | (0.0249) |
| Tropical Livestock | 0.985 | 1.006 | 1.036** | 1.009 |
| Units (TLU) | (0.0148) | (0.0139) | (0.0167) | (0.00919) |
| Marital status | 1.002 | 0.917 | 0.860* | 0.931 |
| | (0.0744) | (0.0709) | (0.0667) | (0.0462) |
| Income | 0.982 | 0.994 | 0.982 | 0.988 |
| (‘0000) | (0.0155) | (0.0121) | (0.0116) | (0.00810) |
| 50% | | | | 1.642*** |
| probability | | | | (0.260) |
| 70% | | | | 4.756*** |
| probability | | | | (0.828) |

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Individual and household control variables do not seem to explain choice in the pooled data. However, education level, livestock holdings (measured in tropical livestock units or TLU) and marital status explain choice at a 70% probability of good weather. An increase in one year of education increases the combined odds of opting for adaptive and improved seed technologies by 1.07 times relative to the off-farm work option, while an extra TLU score increases the same odds by 1.04. At a 30% probability of good weather, an increase in a year of education increases the odds of opting for off-farm work relative to adaptive and improved seeds, implying prudence given the low probability of good weather.

*Ambiguity aversion and technology choice*

Results for the relationship between ambiguity aversion and technology choice are shown in Table 8, also displayed as proportional odds ratios and with the ambiguity aversion/seeking attitudes standardised to one standard deviation and zero mean. Ambiguity aversion significantly affects choice for the 20%-40% and 10%-50% probability sets, while an ambiguity-seeking attitude affects choice in the 0-100%, 20%-40% and 10%-50% probability sets. For a one standard deviation increase in ambiguity aversion, the odds of opting into off-farm work relative to combined adaptive seed and improved seed technologies are 1.8 times greater when the probability set is 20%-40%, and 1.6 times greater for a 10%-50% probability set.

Table 4-8 Technology Choice under Uncertainty

| VARIABLES | (1) **0-100%** | (2) **20%-40%** | (3) **10%-50%** | (4) **60%-80%** | (5) **50%-90%** | (6) **Pooled** |
|---|---|---|---|---|---|---|
| Ambiguity | 1.217 | 1.812** | 1.592** | 0.973 | 1.105 | 1.267** |
| aversion | (0.246) | (0.434) | (0.333) | (0.197) | (0.224) | (0.141) |
| Ambiguity | 0.675* | 0.666* | 0.575*** | 1.062 | 0.817 | 0.745*** |
| seeking | (0.139) | (0.153) | (0.120) | (0.225) | (0.168) | (0.0841) |
| Initial | 0.989 | 1.409** | 0.865 | 1.006 | 1.053 | 1.048 |
| wealth | (0.143) | (0.213) | (0.122) | (0.148) | (0.152) | (0.0828) |
| Gender | 1.210 | 0.624* | 1.332 | 0.795 | 1.314 | 1.024 |
| | (0.318) | (0.175) | (0.341) | (0.213) | (0.338) | (0.146) |
| Age | 1.008 | 1.008 | 1.006 | 0.997 | 1.000 | 1.004 |
| | (0.00800) | (0.00827) | (0.00800) | (0.00827) | (0.00776) | (0.00436) |
| Occupation | 0.976 | 0.980 | 0.987 | 0.981 | 0.975 | 0.980* |
| | (0.0203) | (0.0214) | (0.0207) | (0.0213) | (0.0205) | (0.0113) |
| Education | 1.003 | 0.956 | 1.016 | 1.055 | 1.014 | 1.009 |
| | (0.0403) | (0.0393) | (0.0419) | (0.0426) | (0.0397) | (0.0220) |
| Household | 0.988 | 1.135* | 1.064 | 0.944 | 1.011 | 1.030 |
| size | (0.0750) | (0.0873) | (0.0796) | (0.0721) | (0.0752) | (0.0425) |
| TLU | 0.991 | 0.922* | 0.993 | 0.909** | 0.952 | 0.953** |
| | (0.0401) | (0.0386) | (0.0370) | (0.0372) | (0.0375) | (0.0205) |
| Marital | 0.987 | 0.992 | 1.010 | 1.048*** | 1.001 | 1.006 |
| status | (0.0137) | (0.0151) | (0.0144) | (0.0177) | (0.0125) | (0.00753) |
| Income | 0.990 | 0.999 | 0.995 | 0.994 | 0.987 | 0.993 |
| (‘0000) | (0.0139) | (0.0148) | (0.0119) | (0.0119) | (0.0119) | (0.00686) |
| 20-40 | - | | | | | 0.446*** |
| probability | | | | | | (0.0719) |
| 10-50 | | | | | | 0.767* |
| probability | | | | | | (0.120) |
| 60-80 | | | | | | 2.025*** |
| probability | | | | | | (0.325) |
| 50-90 | | | | | | 1.269 |
| probability | | | | | | (0.198) |

Standard errors in parentheses

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

The results also show that the ambiguity-seeking participants are opting for the safe option relative to adaptive and improved seed options, especially for the 10%-50% probability set (the odds are about 43% higher for off-farm work relative to the combined odds of adaptive and improved seed options). Compared to their ambiguity-averse counterparts, however, the odds for off-farm work for the ambiguity-seeking are slightly less. For example, for the 20%-40% probability set, the odds for opting for the off-farm option relative to the combined odds of adaptive and improved seed options are 81% for the ambiguity-averse and only 33% for the ambiguity-seeking (1 less 0.67).

Pooling across the probability sets enables us to look at the important aspect of how choices differ with different ranges of probability sets, in addition to attitudes towards ambiguity. In Table 8, the baseline is complete uncertainty, i.e., the 0 to 100% probability set. A reduction in the range of uncertainty from 0-100% to 10%-50% or 20%-40% has the effect of increasing the odds of opting for off-farm work relative to adaptive and improved seed options. An explanation for this could be that farmers are more willing to take risks under a wider probability set (0-100%), which includes high possible probabilities in the set compared to narrower probability sets (20%-40% and 10%-50%), which have low highest-possible probabilities in the set. The result for the 60%-80% probability set seems to confirm this, whereas decreasing the range of uncertainty from 0-100% to 60%-80% has the opposite effect; the odds of opting for combined options of adaptive and improved seed relative to off-farm work are more than twice as high.

### 4.8.3 Demand for weather information under uncertainty

Results show that, on average, participants' WTP was more than N$12.5 for all the uncertainty ranges. The highest range of uncertainty (0-100%) had the highest mean WTP, with the median range (10%-50%; 50%-90%) having the second-highest mean WTP, and the lowest range (20%-40%; 60%-80%) having the least mean WTP (see Figure 6).

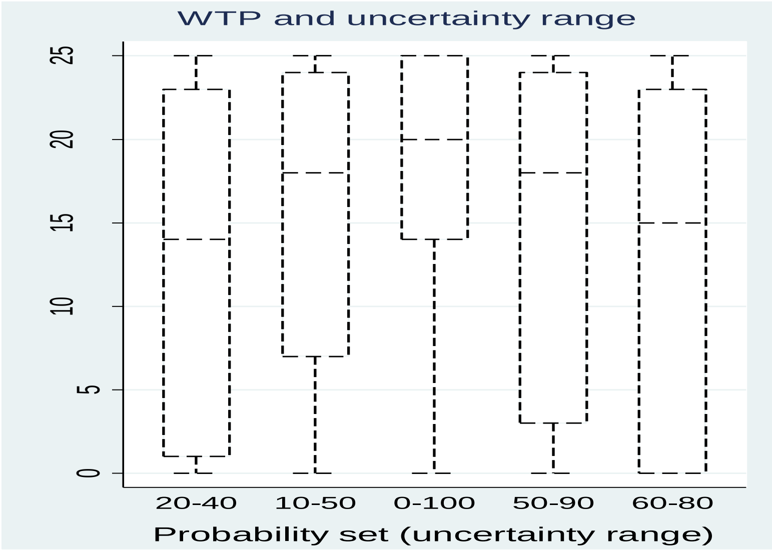


*Figure 4-6 Mean WTP at different uncertainty ranges (probability sets)*

Non-parametric tests show that these differences are significant (see Table 9); the wider the range of uncertainty, the higher the amount participants were willing to pay for information on precise probabilities of good weather. The amount paid in the complete uncertainty round was significantly higher than that paid in any other uncertainty range. In the low probability sets, more was paid in the 10%-50% range than in the 20%-40% probability set, while in the high probability sets, more was paid in the 50%-90% range than in the 60%-80% probability set.

Comparisons between low and high probability sets that have an equal uncertainty range show no significant mean differences in WTP. Participants pay the same for the 20%-40% and 60%-80% probability sets as for the 10%-50% and 50%-90% probability sets. This implies that, under similar uncertainty levels, improving their understanding of the chance of having good weather is equally valuable to the participants.

Table 4-9 Tests for Difference in Mean WTP for Information under Different Uncertainty Ranges

| Range1 (%) | Range2 (%) | Ambiguity averse (t) | Ambiguity neutral/seeking (t) | Overall (t) |
|---|---|---|---|---|
| 0-100 | 20-40 | 4.85*** | 5.56*** | 7.84*** |
| 0-100 | 10-50 | 2.58** | 3.31*** | 5.04*** |
| 0-100 | 60-80 | 5.19*** | 5.30*** | 7.89*** |
| 0-100 | 50-90 | 3.17*** | 3.70*** | 5.76*** |
| 20-40 | 10-50 | -2.18** | -2.22** | -4.01*** |
| 20-40 | 60-80 | 0.33 | -0.11 | 0.15 |
| 20-40 | 50-90 | -1.46 | -1.79* | -2.96*** |
| 10-50 | 50-90 | 0.66 | 0.42 | 1.05 |
| 10-50 | 60-80 | 2.51** | 2.06** | 3.90**** |
| 60-80 | 50-90 | -1.78* | -1.64 | -3.71*** |

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

To complete the analysis,  a comparison between a low probability set with a narrower range, e.g. 20%-40%, and a high probability set with a wider range, e.g. 50%-90%, shows that participants pay more for the latter than the former. Similarly, participants pay more for low probability sets with a wider range, e.g., 10%-50%, compared to a high probability set with a narrower range, e.g.,  60%-80%.

The third and fourth columns show that the mean WTP for ambiguity-averse and ambiguity-seeking/neutral participants are quite similar. Both categories of participants value information similarly and are willing to pay significantly more for information in wider ranges of uncertainty than in narrower ones. One can thus conclude that subjective ambiguity aversion does not seem to be important in explaining willingness to pay for information, but rather the range of uncertainty (objective ambiguity aversion) helps explain WTP. To investigate this further, we ran a regression analysis to see what informs WTP, controlling for observables and attitudes towards uncertainty.

These results are displayed in Table 10. The dependent variable is continuous (0 to 25) indicating the possible range of WTP in the games. Ambiguity aversion/seeking attitudes are as discussed before and a categorical variable for the pooled data regression (last column) indicates the range of uncertainty.

Table 4-10 Determinants of Willingness to Pay for Weather Information

| | (1)<br>**0-100%** | (2)<br>**20%-40%** | (3)<br>**10%-50%** | (4)<br>**60%-80%** | (5)<br>**50%-90%** | (6)<br>**Pooled** |
|---|---|---|---|---|---|---|
| Ambiguity aversion | -0.0232 | 0.0956 | 0.0757 | 0.111 | 0.105 | 0.0379 |
| | (0.0551) | (0.0782) | (0.0711) | (0.0805) | (0.0752) | (0.0479) |
| Ambiguity seeking | 0.0569 | -0.125 | -0.103 | -0.0224 | -0.121 | -0.0120 |
| | (0.0995) | (0.140) | (0.128) | (0.144) | (0.136) | (0.0876) |
| Initial wealth | -0.914* | 0.821 | -0.627 | -0.327 | 0.147 | -0.226 |
| | (0.546) | (0.760) | (0.706) | (0.783) | (0.745) | (0.497) |
| Gender | 0.717 | 0.677 | -0.289 | 0.218 | -0.251 | 0.119 |
| | (0.987) | (1.370) | (1.273) | (1.410) | (1.347) | (0.896) |
| Age | 0.0298 | 0.0325 | 0.0342 | 0.00867 | 0.0139 | 0.0221 |
| | (0.0303) | (0.0420) | (0.0391) | (0.0432) | (0.0413) | (0.0275) |
| Occupation | -0.0258 | -0.114 | -0.0798 | 0.0802 | 0.0778 | -0.0144 |
| | (0.0797) | (0.111) | (0.103) | (0.114) | (0.109) | (0.0726) |
| Education | -0.109 | -0.291 | 0.265 | -0.284 | -0.202 | -0.135 |
| | (0.151) | (0.209) | (0.195) | (0.215) | (0.206) | (0.137) |
| Household size | -0.0758 | 0.434** | 0.335* | -0.246 | -0.102 | 0.0655 |
| | (0.148) | (0.205) | (0.191) | (0.211) | (0.202) | (0.134) |
| TLU | 0.0138 | -0.150** | 0.00979 | -0.0739 | 0.00490 | -0.0387 |
| | (0.0515) | (0.0714) | (0.0665) | (0.0736) | (0.0703) | (0.0468) |
| Marital status | 0.0786 | -0.484 | -0.0413 | 0.170 | -0.544 | -0.151 |
| | (0.281) | (0.390) | (0.364) | (0.402) | (0.384) | (0.256) |
| Income (‘0000) | -0.0142 | -0.0494 | -0.0963 | -0.0418 | 0.0555 | -0.0295 |
| | (0.0474) | (0.0657) | (0.0612) | (0.0676) | (0.0647) | (0.0431) |
| 20-40 probability | - | - | - | - | - | -5.334***<br>(0.628) |
| 10-50 probability | - | - | - | - | - | -2.844***<br>(0.628) |
| 60-80 probability | - | - | - | - | - | -5.436***<br>(0.628) |
| 50-90 probability | - | - | - | - | - | -3.448***<br>(0.627) |

Standard errors in parentheses

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

The analysis confirms that attitudes toward uncertainty do not affect participants’ WTP but the level of uncertainty does. Specifically, compared to the baseline probability set category (0-100%), a probability set of 20-40% receives N$5.3 lower in WTP while a 50%-90% probability set receives N$3.4 lower. These results underscore the value of weather information to farming households, irrespective of their subjective attitudes towards ambiguity.

### 4.8.4 Choice after receiving uncertainty-reducing information

As explained under the section on methods, the information (precise probability) given to participants was randomly generated based on the probability set under consideration. It is interesting to see whether decisions made before the information games *(*series *4* of the games) were significantly different from those made after the information games, whether or not a participant received information. While the preceding discussion shows that farmers value weather information, it is interesting to see what they would do with this information, i.e., whether assessing weather information leads to a change in technology choice and whether that change is welfare-improving.

Non-parametric tests show that in all but one of the rounds, the choices made before and after receipt of information are significantly different for participants who received information (see Table 11). This is very similar for participants who did not receive information, with the choices made before and after the information games being significantly different in three out of the five uncertainty ranges (note that all participants made choices after the information games, whether or not they received information on precise probabilities of good weather outcomes). For the lower probability sets (20%-40% and 10%-50%), participants became conservative in their choices after the information games, whether or not they received information.

Conversely, in the probability sets with high possible probabilities of good weather (0-100%, 60%-80% and 50%-90%), riskier but high-yielding technologies were chosen after the information round for participants who received information. Those who did not receive information changed their choice only for the complete uncertainty probability set (0-100%).

Table 4-11 Test for Difference in Choice before and after Information

| Probability set **(%)** | Received information | | Did not receive information | |
|---|---|---|---|---|
| | z | Prob > \|z | z | Prob > \|z\| |
| 20-40 | 0.360 | 0.7189 | 2.544 | 0.0110 |
| 10-50 | 3.296 | 0.0010 | 2.835 | 0.0046 |
| 0-100 | -1.824 | 0.0682 | -1.734 | 0.0829 |
| 60-80 | -2.060 | 0.0394 | -1.239 | 0.2152 |
| 50-90 | -2.234 | 0.0255 | -1.334 | 0.1821 |

The results imply that technology uptake is higher when farmers have access to weather information, especially if this indicates higher chances of good weather, compared to a situation where the chances are not known precisely. In the case where the chances of good weather are low, weather information can help farmers avoid losses by choosing adaptive technologies or other safer options.

To ground these conclusions further, analysis is required on whether access to information actually made the recipients better off as a result of their choices, since non-recipients of information also changed their before and after information choices. To do this, we use the randomly generated precise probability revealed to the qualifying participants to calculate the expected payoffs after the information rounds for both the recipients and non-recipients of information. These are then compared to the expected payoffs before the information games, calculated using the expected probability for each of the probability sets. The results of this analysis are shown in Table 12.

Table 4-12 Comparison of Expected Payoffs of Choice before and after Information

| Uncertainty range | Received information | | | | Did not receive information | | |
|---|---|---|---|---|---|---|---|
| **(%)** | Expected payoff *before* information | Expected payoff *after* information | t | Mean information cost | Expected payoff *before* information | Expected payoff *after* information | t |
| 20-40 | 66.65 | 65.34 | 0.54 | 8.70 | 66.24 | 68.99 | -1.15 |
| 10-50 | 61.02 | 68.17 | -1.09** | 10.70 | 61.68 | 63.29 | -0.45 |
| 0-100 | 91.45 | 105.88 | -2.35** | 9.77 | 97.78 | 101.75 | -0.38 |
| 60-80 | 128.79 | 132.0 | -0.71 | 10.60 | 133.51 | 135.68 | -0.48 |
| 50-90 | 130.61 | 133.96 | -0.61 | 11.36 | 118.51 | 118.54 | -0.005 |

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

Providing information to participants enabled them to make choices with higher expected payoffs for the complete uncertainty (0-100%) and 10%-50% uncertainty range scenarios. The sub-sample of non-recipients of information made no welfare-improving changes in their before and after choices for any of the uncertainty ranges. The most important point of these results is that in cases where real losses are imminent with low chances of good weather, providing information helps people make welfare-improving changes. This is more so with high levels of uncertainty and very low possible probabilities of good weather, as exemplified in the 10%-50% and 0-100% probability sets. This is intuitive, since providing information would not matter much for welfare if the possible chances of good weather were all high, for example in the 60%-80% and 50%-90% probability sets. The same intuition follows in the case of the 20%-40% probability set, where, no matter the information provided, everything points to low chances of good weather and hence the best response is to use the safest technology.

We complete the analysis by considering whether the decisions made to buy information at a particular cost by the participants are rational. Considering only the uncertainty ranges that resulted in welfare-improving changes after purchase of information, the 0-100% uncertainty range seems the most cost-effective, in that participants spent N$10 on average and gained an extra N$14. However, as stated earlier, climate information is a public good given freely by government and sometimes by development aid organizations. The aim of this piece was to look at whether the level of uncertainty matters for decision making, whether there is actual demand for weather information, and whether accessing weather information improves welfare.

### 4.9 Conclusion and policy implications

The link between behavioural attitudes and technology adoption has been unequivocally established in the literature. In agriculture, subjective attitudes toward uncertainty (ambiguity aversion) have been shown to play an important role in diminishing agricultural technology diffusion among the poor in rural households (Barham at al., 2014; Elabed and Carter, 2015). Others show that ambiguity aversion leads to lower well-being outcomes (e.g. Cardenas and Carpenter, 2013). Our study extends this strand of literature by showing that information that reduces the uncertainty level (objective uncertainty) leads to increased take-up of risky but high-yielding technologies and can thus be used to help ambiguity-averse farmers overcome their inertia in improved technology adoption. We also show that, with access to information, farmers make welfare-improving choices in technology. In the increasingly uncertain environment due to climate change, these results are important for policy. Available weather information that reduces uncertainty in seasonal outcomes can be a clear pathway towards resilience in agricultural production in regions most affected by climate change.

Borrowing from emerging theoretical literature on the importance of objective uncertainty in decision making (e.g. Klibanoff et al., 2005), the analysis begins by showing how objective uncertainty (level of uncertainty) in addition to subjective uncertainty (ambiguity aversion) affects technology choice. In the next step, the study shows that there is a clear demand for uncertainty-reducing information (weather information) among both ambiguity-averse and ambiguity-seeking farmers. The wider the uncertainty, the higher the demand for information, implying the critical role played by uncertainty levels in farming decisions.

In the final step of the analysis, we show that expected payoffs of technology choices without information differ significantly from expected payoffs of choices with information. Farmers who access information make welfare-improving choices compared to those who don't, especially when there is a threat of a climate catastrophe such as drought. The results show that these gains in welfare are also cost-effective, considering the amount spent by farmers to acquire the information. This is despite the fact that such information ought to be a public good. This demonstrates the clear gains in investing in such a policy of climate (weather) information.

**References**


Akay, A., Martinsson, P., Medhin, H., & Trautmann, S. T. (2012). Attitudes toward uncertainty among the poor: An experiment in rural Ethiopia. *Theory and Decision*, *73*(3), 453–464. https://doi.org/10.1007/s11238-011-9250-y

Alpizar, F., Carlsson, F., & Naranjo, M. A. (2011). The effect of ambiguous risk, and coordination on farmers' adaptation to climate change - A framed field experiment. *Ecological Economics*, *70*(12), 2317–2326. https://doi.org/10.1016/j.ecolecon.2011.07.004

Andrews, T. M., Delton, A. W., & Kline, R. (2018). High-risk high-reward investments to mitigate climate change. *Nature Climate Change*, *8*(10), 890–894. https://doi.org/10.1038/s41558-018-0266-y

Barham, B. L., Chavas, J. P., Fitz, D., Salas, V. R., & Schechter, L. (2014). The roles of risk and ambiguity in technology adoption. *Journal of Economic Behavior and Organization*, *97*, 204–218. https://doi.org/10.1016/j.jebo.2013.06.014

Becker, G. M., Degroot, M. H., & Marschak, J. (1964). Measuring Utility by a Single-Response Sequential Method. *Systems Research & Behavioural Science*, *9*(3), 226–232.

Becker, S. W., & Brownson, F. O. (1964). What Price Ambiguity? or the Role of Ambiguity in Decision-Making. *Journal of Political Economy*, *72*(1), 62–73. https://doi.org/10.1073/pnas.0703993104

Brick, K., & Visser, M. (2015). Risk preferences, technology adoption and insurance uptake: A framed experiment. *Journal of Economic Behavior and Organization*, *118*, 383–396. https://doi.org/10.1016/j.jebo.2015.02.010

Cardenas, J. C., & Carpenter, J. (2013). Risk attitudes and economic well-being in Latin America. *Journal of Development Economics*, *103*(1), 52–61. https://doi.org/10.1016/j.jdeveco.2013.01.008

Cole, S., Giné, X., & Tobacman, J. (2013). Barriers to household risk management: evidence from India. *American Economic Journal: Applied Economics*, *5*(1), 104–135.

Di Falco, S., Veronesi, M., & Yesuf, M. (2011). Does Adaptation to Climate Change Provide Food Security? A Micro-Perspective from Ethiopia. *American Journal of Agricultural Economics*, *93*(3), 829–846. https://doi.org/10.1093/ajae/aar006

Eckel, C. C., & Grossman, P. J. (2002). Sex Differences and Statistical Sterotyping in Attitudes Towards Financial Risk. *Evolution and Human Behavior*, *23*(4), 281–295. https://doi.org/10.1016/S1090-5138(02)00097-1

Elabed, G., & Carter, M. R. (2015). Compound-risk aversion, ambiguity and the willingness to pay for microinsurance. *Journal of Economic Behavior and Organization*, *118*, 150–166. https://doi.org/10.1016/j.jebo.2015.03.002

Ellsberg, D. (1961). Risk, Ambiguity, and the Savage Axioms. *Quarterly Journal of Economics*, *75*(4), 643–669. https://doi.org/Article

Feder, G., & Umali, D. . (1993). The adoption of agricultural innovations: A review. *Technological Forecasting and Social Change*, *43*(3–4), 215–239.

Ghirardato, P., Maccheroni, F., & Marinacci, M. (2004). Differentiating ambiguity and ambiguity attitude. *Journal of Economic Theory*, *118*(2), 133–173. https://doi.org/10.1016/j.jet.2003.12.004

Gilboa, I., & Schmeidler, D. (1989). Maxmin Expected Utility with Non-unique Prior. *Journal of Mathematical Economics*, *18*, 141–153.

Giné, X., & Yang, D. (2009). Insurance, credit, and technology adoption: Field experimental evidencefrom Malawi. *Journal of Development Economics*, *89*(1), 1–11. https://doi.org/10.1016/j.jdeveco.2008.09.007

Hayashi, T., & Wada, R. (2010). Choice with imprecise information: An experimental approach. *Theory and Decision*, *69*(3), 355–373. https://doi.org/10.1007/s11238-008-9119-x

Jumare, H., Visser, M., & Brick, K. (2018). Risk preferences and the poverty trap: A look at farm technology uptake among smallholder farmers in the Matzikama Municipality. In *Economic Research Southern Africa*. https://doi.org/10.4324/9781315149776

Klibanoff, P., Marinacci, M., & Mukerji, S. (2005). A Smooth Model of Decision Making under Ambiguity. *Econometirca*, *73*(6), 1849–1892. https://doi.org/10.1111/j.1468-0262.2005.00640.x

Liebenehm, S., & Waibel, H. (2014). Simultaneous estimation of risk and time preferences among small-scale cattle farmers in West Africa. *American Journal of Agricultural Economics*, *96*(5), 1420–1438. https://doi.org/10.1093/ajae/aau056

Mason, S., Kruczkiewicz, A., Ceccato, P., & Crawford, A. (2015). *Accessing and Using Climate Data and Information in Fragile , Data-Poor States*. (May), 1–27. Retrieved from https://www.iisd.org/sites/default/files/publications/accessing-climate-data-information-fragile-data-poor-states.pdf

Mcintosh, C., Povell, F., & Sadoulet, E. (2015). *Utility, Risk, and Demand for Incomplete Insurance: Lab Experiments with Guatemalan Cooperatives *.*

Mendelsohn, J., Jarvis, A., Roberts, C., & Robertson, T. (2002). *The Atlas of Namibia: A Potrait of the land and its people*.

Njau, L. N. (2010). Seasonal-to-interannual climate variability in the context of development and delivery of science-based climate prediction and information services worldwide for the benefit of society. *Procedia Environmental Sciences*, *1*(1), 411–420. https://doi.org/10.1016/j.proenv.2010.09.029

Pretty, J., Toulmin, C., & Williams, S. (2011). Sustainable intensification in African agriculture. *International Journal of Agricultural Sustainability*, *9*(1), 5–24. https://doi.org/10.3763/ijas.2010.0583

Reid, H., Sahlen, L., Stage, J., & MacGregor, J. (2007). The Economic Impact of climate change in Namibia. *Environmental Economics Programme Discussion Paper 07-02*, (November), 1–54.

Ross, N., Santos, P., & Capon, T. (2012). Risk , Ambiguity and the Adoption of New Technologies : Experimental Evidence from a developing economy *. *International Association of Agricultural Economists*, (October), 30 p. Retrieved from http://ageconsearch.umn.edu/bitstream/126492/2/Nross_last_IAAE.pdf

Singh, C., Daron, J., Bazaz, A., Ziervogel, G., Spear, D., Krishnaswamy, J., … Kituyi, E. (2017). The utility of weather and climate information for adaptation decision-making: current uses and future prospects in Africa and India. *Climate and Development*, *0*(0), 1–17. https://doi.org/10.1080/17565529.2017.1318744

Tadross, M., & Johnston, P. (2012). *Climate Systems Regional Report : Southern Africa August 2012*.

Takahashi, K. (2013). The roles of risk and ambiguity in the adoption of the system of rice intensification (SRI): Evidence from Indonesia. *Food Security*, *5*(4), 513–524. https://doi.org/10.1007/s12571-013-0270-z

Tall, A., Coulibaly, J. Y., & Diop, M. (2018). Do climate services make a difference? A review of evaluation methodologies and practices to assess the value of climate information services for farmers: Implications for Africa. *Climate Services*, *11*(June), 1–12.

https://doi.org/10.1016/j.cliser.2018.06.001

Tonsor, G. T. (2018). Producer decision making under uncertainty: Role of past experiences and question framing. *American Journal of Agricultural Economics*, *100*(4), 1020–1135. https://doi.org/10.1093/ajae/aay034

Yates, J. F., & Zukowski, L. G. (1976). Characterization of Ambiguity in Decision-Making. *Behavioral Science*, *21*, 19–25.

## Appendix: Experiment design and protocols

[Large posters including visual aids like flash cards were used for the graphics as presented here to support the explanations]

### INTRODUCTION

My name is [NAME], and I am a researcher with [UNIVERSITY 1 NAME] and [UNIVERSITY 2 NAME]. These are my colleagues [NAMES]. We have invited you here so you can participate in an experiment with games where you have the opportunity to earn money based on the decisions you make.

### INITIAL ENDOWMENT

There are several games in this experiment. You will have the opportunity to earn money in the course of playing these games today. **It is also possible to lose some money in some of these games**. For this reason we will give you a start-up amount of money (which we will call your *initial wealth*) before starting the games, equal to N$150. The money you will receive as your initial wealth is enough to cover any of these losses that you may incur. Any additional money you earn in the game and also any amount of initial wealth that you don't spend on losses, you can keep and take home with you at the end of this session.

How much money you earn today depends on the decisions you make during the games. That is why it is very important that you understand the rules of the games, which I am going to explain to you as we go along. **The money you earn today from the games will be paid to you at the end of the whole session in cash.**

You play these games as individuals, not in groups. So please don't talk to anyone while we are playing the games. If you have **ANY** questions at any stage you can just raise your hand and someone will come and answer your question privately.

The exercise today will take three-four hours. **Participation in the sessions is voluntary**. If you decide not to take part, you may leave at any time, even after you have started playing – **but then you will not earn any money**. If you prefer to stay we ask that you sign the form that our assistants are bringing around right now indicating your consent to participate in the games.

[HAND OUT THE CONSENT FORMS]

This form says that you understand participation in these games is voluntary and that you can leave whenever you want to. **But if you do leave before we have finished playing all the games, you won't receive any money**.

Is everyone finished signing the forms? Ok, someone is going to come around and collect the forms from you. [COLLECT FORMS]

### The Games

As I have said, we will be playing games with real money. At the end of the day, whatever money you have earned is yours to keep and take home.

Let's talk about how today will work. There are **four** parts in this experiment; part one has **two** games, part two has **three** games and part three to four each has **five** games. Most of these games are quite similar as we will see. Everyone will play all the games today. We will indicate on the [poster] which games we have played and which are remaining as we go on.

[POINT TO THE POSTER AS YOU EXPLAIN THIS]

| Part 1 | Part 2 | Part 3 | Part 4 (a & b) |
|---|---|---|---|
| Game 1 | Game 1 | Game 1 | Game 1 |
| Game 2 | Game 2 | Game 2 | Game 2 |
| | Game 3 | Game 3 | Game 3 |
| | | Game 4 | Game 4 |
| | | Game 5 | Game 5 |

Besides the initial wealth that was allocated to you at the start of the session, **you will also earn money from two of these games; from one game in Part I and any one game from Parts 2 to 4.** You will only find out which of these games you will be paid for at the **end of the session!** So it is important to play **all games as if real money is at stake in every game**. In total you stand to earn between N$50 and N$375 for today's activities. Your earnings depend on the choices you make in the games.

**PART 1: RISK AND AMBIGUITYAVERSION**

I am now going to explain the rules of games in Part one

**Game 1: 50% probability of High outcome**

| Gamble | Payoffs | | ✓ |
|---|---|---|---|
| | Low outcome | High outcome | |
| 1 | 24 | 24 | |
| 2 | 18 | 36 | |
| 3 | 12 | 48 | |
| 4 | 6 | 60 | |
| 5 | 0 | 72 | |

This poster is a large version of the sheet of paper that is in front of you.

In this game, you must choose from among the 5 gambles [REFER TO POSTER]. There are two payoffs for each of these gambles; Low outcome and High outcome.

If you choose Gamble 1, you will earn N$24 whether the game results in a Low or High outcome. If you choose Gamble 2, you will earn N$18 if the game results in a Low outcome and N$36 if the game results in a High outcome. If you choose Gamble 3, you will earn N$12 if the game results in a Low outcome and N$48 if the game results in a High outcome. If you choose Gamble 4, you will earn N$6 if the game results in a Low outcome and N$60 if the game results in a High outcome. If you choose Gamble 5, you will earn N$0 if the game results in a Low outcome and N$72 if the game results in a High outcome.

As you can see, the amounts earned from the Low outcome decreases as you move from Gamble 1 through to Gamble 5; it has decreased from N$24 in Gamble 1 to zero in Gamble 5. On the other hand, the amount earned from the High outcome increases as you move from Gamble 1 through to Gamble 5; It has increased from N$24 in Gamble 1 to N$72 in Gamble 5. To illustrate, if you choose Gamble 1, you will earn N$24 whether the game results in High or Low outcome but if you choose Gamble 5, you will earn N$72 if the game results in a High outcome and earn nothing if the game results in a Low outcome! [EXPLAIN EARNINGS FOR THE OTHER GAMBLES]

To determine whether the game results in a Low or High outcome, we are going to draw a ball from this bag [SHOW THE BAG]. There are 10 balls in the bag; FIVE black balls and FIVE white balls. If we draw a BLACK ball, then the outcome of the game is High and if we draw a WHITE ball, the outcome of the game is Low.

[DEMONSTRATE DRAWING THE BALL AND INDICATE POSSIBLE EARNINGS]

Does anyone have any questions before we start?

Ok, let's start. Please write the number we gave you at the start of the experiment on the sheet where it says experiment number [SHOW WHERE THEY MUST PUT THEIR NUMBER].

Please tick beside the gamble you prefer.

**Game 2: Uncertain probability of High outcome**

This game is similar to the one you have just played. The main difference in this game however is that the **number of BLACK and WHITE balls in the bag is UNKNOWN**. Just like before, you must choose from among the 5 gambles. Once again, there are two payoffs for each of these gambles; Low outcome and High outcome. The BLACK ball is still the one indicating High outcome if drawn.

Just like before, you have a sheet before you resembling the poster in front [POINT AT POSTER]. You will tick beside the gamble you prefer.

Remember, you now have to make your choices without knowing the number of black or white balls in the bag. At the end of today's session, if we draw this game as the game we are paying you for, we will reveal how many black balls there are in the bag and then make a draw to see if the outcome for the game is High or Low.

I have with me a spinning wheel with different slices and an arrow with a pointer on top. Each slice on the wheel contains a picture of a bag with 10 balls in different combinations of black and white; these range from zero black and ten white balls in the bag to ten black and zero white balls. We are going to spin this wheel and the ball combination that comes under the pointer indicates the number of black and/or white balls that we are going to put in the bag.

After putting these balls in the bag, one of you will then come up and draw one ball from the bag. **Remember the bag will only contain TEN balls, and that if a black ball is drawn the game outcome is High and if the drawn ball is WHITE, the game outcome is Low.**

Are there any questions? [CHECK TO SEE ALL HAVE UNDERSTOOD]

Please write the number we gave you at the start of the experiment on the sheet where it says experiment number [GESTURE TO WHERE THEY MUST PUT THEIR NUMBER].

Please tick beside the gamble you prefer.

**PART 2-4: Choice of Off-Farm Work *OR* Farming using Improved or Adaptive Seeds in an Uncertain Weather Environment**

**Preamble**

Before we start let's talk about some of the decisions you make in your daily life and particularly when it comes to farming decisions. Different periods during the year often calls for certain decisions to be made. For example, during rainy seasons, you may have to decide if you are going to cultivate crops during that season or just undertake off-farm activities (such as working on a government project), if these are available. You may also opt to undertake a mix of these activities. In case you decide to cultivate crops, you also have to decide on the type of inputs you have to use, key among these being the type of seeds you are going to plant. You may decide to use improved (hybrid) seed, which normally give a very good return when there are enough rains during that season, but can also perform very poorly in case the rains are not enough or are too much. On the other hand, you may also decide to plant seeds that are specifically bred to withstand weather stress (drought or floods). Thus decisions that us as farmers make during this period are greatly influenced by our expectations about the weather. For example, if we have reason to believe that the rains are going to be good, then we are better off using the improved seeds, while on the other hand if we believe the rains will not be adequate, then we would better use the adaptive seeds. In case we have off-farm activities, we may just decide not to undertake any crop farming that season. It might also be the case that someone decides to use a bit of each of these; for example plant some improved seed in some plots while in others plant adaptive seed, or do crop cultivation while still involved in an off farm activity.

In the games we will play now, you will be tasked with making decisions involving such choices which are similar to what you are doing in your day to day life. However, in this game setting we are going to assume that you only make one choice per season; choosing to devote your time to off-farm activities or to engage in crop farming where you will either choose to plant improved seeds OR drought resistant seeds.

**Weather information**

Understanding the weather patterns for each season is important for farmers in order to decide what to plant. While decades of farming experience helps to understand the weather patterns, some farmers also rely on traditional methods able to predict the weather. From time to time, we receive outside information from government agencies and researchers that tell us PRA the weather is going to be like in a particular season i.e. whether it's going to rain or not. Such information is often given by government agencies free of charge. Sometimes this information is lacking and farmers have to rely on their experience in farming to decide what to plant for the coming season, not knowing exactly what the weather will be like. While it may not be possible to predict EXACTLY what the weather will be like in a coming season, knowing the CHANCE of having good rainfall or drought in the coming season is helpful in making decisions of what to plant.

In this game we will also give information about the CHANCE of having good or bad weather to help you make decisions.

**Instructions**

In the following series of games, in each game you are given a choice between three options; working in an off farm activity, or choosing to engage in crop farming where you either choose to plant seeds adapted to harsh weather "adaptive seeds", or you choose to plant improved seeds. While in real life it may be possible to do more than one such activity at a time, let us for now assume that only one of these can be undertaken at a time.

What you earn from the off farm activity is not affected by weather outcomes and has a constant payoff in good and bad weather.

The improved seed on the other hand has very high yields if the rainfall is good but in the event of low rainfall or droughts, it is possible to make losses given the cost of inputs. On the other hand, the seed variety adapted to dry weather conditions has somewhat lower yields than the improved seeds during good rainfall, but on the upside, when there is a drought it still gives positive yields (although lower than for good rains).

Your task is to choose whether to farm or do off-farm work, and if you farm which seed type to plant. You are told that the chance of good rainfall is not known with certainty. Instead, you will be given information about the chance of there being good rainfall or a drought to help with your decision making. The chance of getting a good or a bad weather outcome will be presented by a bag with black and white balls, where if we draw a black ball from the bag it indicates good rainfall and if we draw a white ball it represents bad rainfall or drought conditions.

In some of these games you will be asked to make your decision without having much information about the weather conditions. In other games we will give you the option to buy information about the chance of having good or poor rainfall which could help you to make better decisions.

**Experiment number:_________**

| | **Weather** | | ✓ |
|---|---|---|---|
| |  |  | |
| Off-farm work | **75** | **75** | |
| Adaptive seeds | **150** | **25** | |
| Improved seeds | **225** | **-25** | |

**Part 2: Risk Games**

**Game 1: 30% probability of good weather**

You are going to make a choice among three livelihood options; off-farm work, farming using seeds adapted to harsh weather “adaptive seeds” or farming using improved seeds. [POINT TO POSTER]. The pay offs for each choice depend on how the weather turns out to be in this season.

Note that you are only going to make ONE CHOICE; so you either have to choose off-farm work; farming using adaptive seeds or farming using improved seeds. The off farm work option has constant payoffs, meaning it does not matter what the weather turns out to be, you always get N$75. On the other hand, for the adaptive seed option you earn N$150 if the season has good rains or N$25 if the rainfall is poor. So it has a higher payoff in case of good weather than in the case of bad weather, but you still get to earn some money either way. The improved seed option will give a very high pay off if its good weather but if the weather is bad you will make a loss (N$225 in case of good rains or –N$25 in case of bad rains).

To determine whether the season will have good rainfall (good weather) or poor rainfall (bad weather), we are going to make a draw from TEN balls in this bag. The bag contains THREE black and SEVEN white balls. A draw of a BLACK ball implies that the season has GOOD rains, while a draw of a WHITE ball implies the season has BAD rains or drought conditions.

[DEMONSTRATE DRAWING THE BALLS AND IMPLICATION ON EARNINGS]

EXAMPLE: So, if you choose the off-farm activity option, you will earn N$75 whether the colour of the ball we draw is black or white (whether good or bad weather). If you choose the adaptive seeds **and** we draw a black ball (good weather), you earn N$150, but if we draw a white ball (bad weather), you earn N$25. Let's say you choose the improved seed option and we draw a black ball (good weather), you earn N$225. If we draw a white ball (bad weather), **you incur a debt of N$25!**

Are there any questions? [CHECK TO SEE ALL HAVE UNDERSTOOD]

Please write the number we gave you at the start of the experiment on the sheet where it says experiment number [GESTURE TO WHERE THEY MUST PUT THEIR NUMBER], then mark next to your choice. **You can only choose one of these options!**

**Game 2: 50% probability of good weather**

Again you are going to make a choice among three livelihood options; off-farm work, farming using seeds adapted to harsh weather "adaptive seeds" or farming using improved seeds. [POINT TO POSTER]. The pay offs for each choice depend on how the weather turns out to be in this season.

Just like previous time, you are only going to make ONE CHOICE; so you either have to choose off-farm work; farming using adaptive seeds or farming using improved seeds. The off farm work option has constant payoffs, meaning it does not matter what the weather turns out to be, you always get N$75. On the other hand, for the adaptive seed option you earn N$150 if the season has good rains or N$25 if the rainfall is poor. So it has a higher payoff in case of good weather than in the case of bad weather, but you still get to earn some money either way. The improved seed option will give a very high pay off if its good weather but if the weather is bad you will make a loss (N$225 in case of good rains or –N$25 in case of bad rains).

To determine whether the season will have good rainfall (good weather) or poor rainfall (bad weather), we are going to make a draw from TEN balls in this bag. The bag now contains FIVE black and FIVE white balls. A draw of a BLACK ball implies that the season has GOOD rains, while a draw of a WHITE ball implies the season has BAD rains or drought conditions.

[DEMONSTRATE NUMBER OF BALLS IN BAG AND DRAW IMPLICATIONS]

Are there any questions? [CHECK TO SEE ALL HAVE UNDERSTOOD]

Please write the number we gave you at the start of the experiment on the sheet where it says experiment number [GESTURE TO WHERE THEY MUST PUT THEIR NUMBER], then mark next to your choice. **You can only choose one of these options!**

**Game 3: 70% probability of good weather**

Again you are going to make a choice among three livelihood options; off-farm work, farming using seeds adapted to harsh weather "adaptive seeds" or farming using improved seeds. [POINT TO POSTER]. The pay offs for each choice depend on how the weather turns out to be in this season.

Just like previous time, you are only going to make ONE CHOICE; so you either have to choose off-farm work; farming using adaptive seeds or farming using improved seeds. The off farm work option has constant payoffs, meaning it does not matter what the weather turns out to be, you always get N$75. On the other hand, for the adaptive seed option you earn N$150 if the season has good rains or N$25 if the rainfall is poor. So it has a higher payoff in case of good weather than in the case of bad weather, but you still get to earn some money either way. The improved seed option will give a very high pay off if its good weather but if the weather is bad you will make a loss (N$225 in case of good rains or –N$25 in case of bad rains).

To determine whether the season will have good rainfall (good weather) or poor rainfall (bad weather), we are going to make a draw from TEN balls in this bag. The bag now contains SEVEN black and THREE white balls. A draw of a BLACK ball implies that the season has GOOD rains, while a draw of a WHITE ball implies the season has BAD rains or drought conditions.

[DEMONSTRATE NUMBER OF BALLS IN BAG AND DRAW IMPLICATIONS]

Are there any questions? [CHECK TO SEE ALL HAVE UNDERSTOOD]

Please write the number we gave you at the start of the experiment on the sheet where it says experiment number [GESTURE TO WHERE THEY MUST PUT THEIR NUMBER], then mark next to your choice. **You can only choose one of these options!**

**Part 3: Uncertainty Games**

The games in this part are similar to ones you just completed. The only difference is that unlike before, the probability of good weather is now not known precisely. You will make decisions based on information given in each game indicating the possible range within which the precise probability of good weather might lie.

**Game 1: 0-100% probability of good weather**

Again, you are going to make a choice among three livelihood options; off-farm work, farming using seeds adapted to harsh weather “adaptive seeds” or farming using improved seeds. [POINT TO POSTER]. The pay offs for each choice depend on how the weather turns out to be in this season.

Just like before, to determine whether the season will have good rainfall (good weather) or poor rainfall (bad weather), we are going to make a draw from TEN balls in this bag, where a BLACK ball implies that the season has GOOD rains and a draw of a WHITE ball implies the season has BAD rains or drought conditions**.** In this game however, **we do not know how many white or black balls are in the bag**. In other words, we do not know precisely what the chances are of the weather in a season being good, or being bad.

After you have each made a choice among the three livelihood options [POINT AGAIN TO THE POSTER], we will use a spinning wheel to determine the number of black and white balls to put in the bag. We will then make a draw from a bag to determine the weather outcome .

Now, this is how we are going to determine the information on the chance of good or bad weather at the end of the session. I have with me a spinning wheel divided into different segments. On each segment is a picture of a bag containing 10 balls with different combinations of black and white balls. We are going to spin this wheel and the when the wheel stops turning, the picture that ends up under this arrow indicates the number of black and/or white balls that we must put in the bag.

[DEMONSTRATE USING THE SPINNING WHEEL]

**Remember the bag will only contain TEN balls, and that if a black ball is drawn it indicates good weather.** If the arrow points at the bag with no black balls, we are going to put ten white balls in the bag, and no black ball, meaning that there will be no chance of good rains this season. If the arrow points at the bag with 10 black balls, we are going to put ten black balls in the bag and no white ball, meaning there is no chance of bad rains this season. If the arrow points to the bag with five black balls, we are going to put five black balls in the bag and five white balls, meaning there is an even chance of good rains this season. This is similar for all other numbers on the wheel. [REPEAT THIS SECTION].

Are there any questions? [CHECK TO SEE ALL HAVE UNDERSTOOD]

Please write the number we gave you at the start of the experiment on the sheet where it says experiment number [GESTURE TO WHERE THEY MUST PUT THEIR NUMBER], then mark next to your choice. **You can only choose one of these options!**

**Game 2: 20% to 40% probability of good weather**

This game is similar to one played before. The only difference is that now we have some information of the range of probabilities within which good rains may occur in the season. To demonstrate this chance of good weather, the bag will contain either two black and eight white balls, three black and seven white balls, OR four black and six white ball. [DEMONSTRATE THIS]. Just like before, a draw of a BLACK ball implies that the season has GOOD rains, while a draw of a WHITE ball implies the season has BAD rains.

**Again, we will use a spinning wheel to determine the number of black and white balls to put in the bag. We will then make a draw from a bag to determine the weather outcome.**

The spinning wheel now is divided into different segments each with a picture of a bag containing TEN balls ranging from two to four black balls. We are going to spin this wheel and when the wheel stops turning, the picture that ends up under this arrow indicates the number of black and white balls that we must put in the bag. **Remember the bag will only contain TEN balls, and that if a black ball is drawn it indicates good weather.** If the arrow points at the bag with two black balls, we are going to put two black and eight white balls in the bag, meaning that there will be a very small chance of good rains this season. If the arrow points at the bag with three black balls, we are going to put three black and seven white balls in the bag, meaning there is a small chance of good rains this season. If the arrow points to the bag with four black balls, we are going to put four black and six white balls in the bag, meaning there is a somewhat larger chance of good rains this season. This is similar for all other numbers on the wheel. [REPEAT THIS SECTION].

Are there any questions? [CHECK TO SEE ALL HAVE UNDERSTOOD]

Please write the number we gave you at the start of the experiment on the sheet where it says experiment number [GESTURE TO WHERE THEY MUST PUT THEIR NUMBER], then mark next to your choice. **You can only choose one of these options!**

**Game 3: 10% to 50% probability of good weather**

This game is similar to one played before. The only difference is that now we have some information of the range of probabilities within which good rains may occur in the season. To demonstrate this chance of good weather, the bag will contain either one black and nine white balls, two black and eight white balls, three black and seven white balls, four black and six white balls OR five black and five white balls. [DEMONSTRATE THIS]. Just like before, a draw of a BLACK ball implies that the season has GOOD rains, while a draw of a WHITE ball implies the season has BAD rains or drought conditions.

**Again, we will use a spinning wheel to determine the number of black and white balls to put in the bag. We will then make a draw from a bag to determine the weather outcome.**

The spinning wheel now is divided into different segments each with a picture of a bag containing TEN balls ranging from one to five black balls. We are going to spin this wheel and the when the wheel stops turning, the picture that ends up under this arrow indicates the number of black balls that we must put in the bag. **Remember the bag will only contain TEN balls, and that if a black ball is drawn it indicates good weather.** If the arrow points at the bag with one black ball, we are going to put one black and nine white balls in the bag, meaning that there will be a very small chance of good rains this season. If the arrow points at the bag with two black balls, we are going to put two black and eight white balls in the bag, meaning that there is still a small chance of good rains this season. If the arrow points at the bag with three black balls, we are going to put three black and seven white balls in the bag, meaning there is a somewhat small chance of good rains this season. If the arrow points at the bag with four black balls, we are going to put four black and six white balls in the bag, meaning there is an improved chance of good rains this season. If the arrow points to the bag with five black balls, we are going to put five black and five white balls in the bag, meaning there is an even chance of good or bad rains this season. This is similar for all other numbers on the wheel. [REPEAT THIS SECTION].

Are there any questions? [CHECK TO SEE ALL HAVE UNDERSTOOD]

Please write the number we gave you at the start of the experiment on the sheet where it says experiment number [GESTURE TO WHERE THEY MUST PUT THEIR NUMBER], then mark next to your choice. **You can only choose one of these options!**

**Game 4: 60% to 80% probability of good weather**

This game is similar to one played before. The only difference is that now we have some information of the range of probabilities within which good rains may occur in the season. To demonstrate this chance of good weather, the bag will contain either six black and four white balls, seven black and three white balls, OR eight black and two white balls [DEMONSTRATE THIS]. Just like before, a draw of a BLACK ball implies that the season has GOOD rains, while a draw of a WHITE ball implies the season has BAD rains or drought conditions.

**Again, we will use a spinning wheel to determine the number of black and white balls to put in the bag. We will then make a draw from a bag to determine the weather outcome.**

The spinning wheel now is divided into different segments each with a picture of a bag containing TEN balls ranging from six to eight black balls. We are going to spin this wheel and the when the wheel stops turning, the picture that ends up under this arrow indicates the number of black balls that we must put in the bag. **Remember the bag will only contain TEN balls, and that if a black ball is drawn it indicates good weather.** If the arrow points at the bag with six black balls, we are going to put six black and four white balls in the bag, meaning that there will be a slightly higher chance of good rains this season. If the arrow points to the bag with eight black balls, we are going to put eight black and two white balls in the bag, meaning there is a very high chance of good this season. This is similar for all other numbers on the wheel. [REPEAT THIS SECTION].

Are there any questions? [CHECK TO SEE ALL HAVE UNDERSTOOD]

Please write the number we gave you at the start of the experiment on the sheet where it says experiment number [GESTURE TO WHERE THEY MUST PUT THEIR NUMBER], then mark next to your choice. **You can only choose one of these options!**

**Game 5: 50% to 90% probability of good weather**

This game is similar to one played before. The only difference is that now we have some information of the range of probabilities within which good rains may occur in the season. To demonstrate this chance of good weather, the bag will contain either five black and five white balls, six black and four white balls, seven black and three white balls, eight black and two white balls, OR nine black balls and one white ball [DEMONSTRATE THIS]. Just like before, a draw of a BLACK ball implies that the season has GOOD rains, while a draw of a WHITE ball implies the season has BAD rains or drought conditions.

**Again, we will use a spinning wheel to determine the number of black and white balls to put in the bag. We will then make a draw from a bag to determine the weather outcome.**

The spinning wheel now is divided into different segments each with a picture of a bag containing TEN balls ranging from five to nine black balls. We are going to spin this wheel and the when the wheel stops turning, the picture that ends up under this arrow indicates the number of black balls that we must put in the bag. **Remember the bag will only contain TEN balls, and that if a black ball is drawn it indicates good weather.** If the arrow points at the bag with five black balls, we are going to put five black and five white balls in the bag, meaning that there will be an even chance of good or bad rains this season. If the arrow points to the bag with nine black balls, we are going to put nine black balls and only one white ball in the bag, meaning there is an extremely high chance of good rains this season. This is similar for all other numbers on the wheel. [REPEAT THIS SECTION].

Are there any questions? [CHECK TO SEE ALL HAVE UNDERSTOOD]

Please write the number we gave you at the start of the experiment on the sheet where it says experiment number [GESTURE TO WHERE THEY MUST PUT THEIR NUMBER], then mark next to your choice. **You can only choose one of these options!**

**PART 4: Willingness to Pay for Weather Information and Choice after Information**

**INSTRUCTIONS**

The games in these parts are similar to ones you have been playing. Again, you will be asked to make a decision about three livelihood options (off-farm work, farming using drought resistant or “adaptive seeds” and farming using improved seeds), and as before you have to make this decision not knowing what the exact chances of good weather are. However, this time **you have the option to purchase information that tells you what the chances of good or bad weather are**. By paying for this information, you are going to be given precise information about the chance of getting good or bad rains. You are thus given a chance to play the game knowing the exact number of the black and white balls in the bag.

Like before, we use the spinning wheel to determine the precise probability of good weather; this time however, **we can reveal this information to you before you make your choice, if you pay enough for it**. If you feel that this information will be valuable for you to make your decision, you can use some of your initial wealth to purchase the information. The cost of this weather information ranges from zero to twenty five Namibian dollars (N$0 to N$25).

In the answer sheet given to you, you will indicate the amount you want to put down as payment for this weather information, ranging from N$0 to N$25. After we have collected your answer sheets, we are going to make a draw from this pack of 26 cards in my hand, to determine the actual cost of information. The cards are labelled from 0 to 25 [SHOW THE CARDS WITH NUMBERS WRITTEN ON THEM]. The number on the card that is drawn will be the cost of the weather information.

**Experiment number: _________**

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ✓ | | | | | | | | | | | | | | | | | | | | | | | | | | |

If the amount of money you indicated on the answer sheet **is less than the number on the card that has been drawn, you will not receive weather information.** This means that you will have to make your choice about which of the three livelihood options (off-farm work, farming using drought resistant or “adaptive seeds” and farming using improved seeds) to pick, without having any information about the number of white and/or black balls in the bag. Also, you will not have to pay anything if the amount you indicate on the answer sheet was less than the actual price that we drew from the pack of cards.

On the other hand, if you indicated the amount of money you are willing to pay to receive information **as equal to, or greater than the number on the card we drew from the bag, you will receive information** on the chances of good or bad weather before you choose the livelihood option. In other words, you will be told the number of black and white coloured balls in the bag before you make your choice among the three livelihood options. **The cost of the information (which will range from 0-25) is equal to the number on the card we draw from the pack of cards.** You will pay for this information from your initial wealth.

**Game 1a: WTP for weather information (0%-100% probability range)**

This game is similar to one you played where the chances of good whether are completely unknown. In other words, you have no idea how many black or white balls are in the bag. There could be all black and no white balls in the bag indicating chances of good weather are certain, or there could also be all white balls and no black ball in the bag indicating chances of bad weather are certain. There could be all other different combinations of black and white balls in the bag. [DEMONSTRATE THIS]

You will indicate how much you would like to pay for information to know how many black balls (chances of good weather) there are in the bag **before you make your choice**, in this particular case where the chances are completely unknown.

Are there any questions?

Ok, let’s start. Please write the number we gave you at the start of the experiment on the sheet where it says experiment number [GESTURE TO WHERE THEY MUST PUT THEIR NUMBER].

Indicate (tick) the amount you are willing to pay on the sheet provided.

**Game 1b: Choice after weather information round (0%-100% probability range)**

After your WTP choice and the draw of the actual cost of information, we have determined who is receiving information before making a livelihood choice. If you are among those receiving the information, we are going to hand you an **envelope including a picture of a bag with 10 balls, showing you how many black and white balls there are in the bag**. Do not reveal this picture to anyone else. If you are not receiving information, you will also receive this envelope but there will be no information inside. Everybody will then make their decisions.

Check the envelope handed to you and use the information inside to help you choose a livelihood option, given the chance of good weather as contained in the information in the envelope. If you have received an empty envelope, it means you did not qualify to receive information and are required to make a choice without information on the precise number of black or white balls in the bag.

Are there any questions? [CHECK TO SEE ALL HAVE UNDERSTOOD]

Please write the number we gave you at the start of the experiment on the sheet where it says experiment number [GESTURE TO WHERE THEY MUST PUT THEIR NUMBER], then mark next to your choice. **You can only choose one of these options!**

**Game 2a: WTP for weather information (20%-40% probability range)**

This game is similar to one you just played. You have some information that the chances of good weather lie between 20% and 40%. In other words, there could be two black and eight white balls in the bag, three black and seven white balls in the bag OR four black and six white balls in the bag.  [DEMONSTRATE THIS]

You will indicate how much you would like to pay for information to know precisely how many black balls (chances of good weather) there are in the bag before you make your choice, in this particular case where the chances lie between 20% and 40%.

Are there any questions?

Ok, let's start. Please write the number we gave you at the start of the experiment on the sheet where it says experiment number [GESTURE TO WHERE THEY MUST PUT THEIR NUMBER].

Indicate (tick) the amount you are willing to pay on the sheet provided.

**Game 2b: Choice after weather information round (20%-40% probability range)**

Again, we have determined who is receiving information before making a livelihood choice. Just like before, if you are among those receiving the information, we are going to hand you an envelope including a picture of a bag with 10 balls, showing you how many black and white balls there are in the bag. Do not reveal this picture to anyone else. If you are not receiving information, you will also receive this envelope but there will be no information inside. Everybody will then make their decisions.

Check the envelope handed to you and use the information inside to help you choose a livelihood option, given the chance of good weather as contained in the information in the envelope. If you have received an empty envelope, it means you did not qualify to receive information in this game and are required to make a choice without information on the precise number of black or white balls in the bag.

Are there any questions? [CHECK TO SEE ALL HAVE UNDERSTOOD]

Please write the number we gave you at the start of the experiment on the sheet where it says experiment number [GESTURE TO WHERE THEY MUST PUT THEIR NUMBER], then mark next to your choice. **You can only choose one of these options!**

**Game 3a: WTP for weather information (10%-50% probability range)**

This game is similar to one you just played. You have some information that the chances of good weather lie between 10% and 50%. In other words, there could be one black and nine white balls in the bag, two black and eight white balls in the bag, three black and seven white balls in the bag, four black and six white balls in the bag OR five black and five white balls in the bag.  [DEMONSTRATE THIS]

You will indicate how much you would like to pay for information to know precisely how many black balls (chances of good weather) there are in the bag before you make your choice, in this particular case where the chances lie between 10% and 50%.

Are there any questions?

Ok, let's start. Please write the number we gave you at the start of the experiment on the sheet where it says experiment number [GESTURE TO WHERE THEY MUST PUT THEIR NUMBER].

Indicate (tick) the amount you are willing to pay on the sheet provided.

**Game 3b: Choice after weather information round (10%-50% probability range)**

Again, we have determined who is receiving information before making a livelihood choice. Just like before, if you are among those receiving the information, we are going to hand you an envelope including a picture of a bag with 10 balls, showing you how many black and white balls there are in the bag. Do not reveal this picture to anyone else. If you are not receiving information, you will also receive this envelope but there will be no information inside. Everybody will then make their decisions.

Check the envelope handed to you and use the information inside to help you choose a livelihood option, given the chance of good weather as contained in the information in the envelope. If you have received an empty envelope, it means you did not qualify to receive information in this game and are required to make a choice without information on the precise number of black or white balls in the bag.

Are there any questions? [CHECK TO SEE ALL HAVE UNDERSTOOD]

Please write the number we gave you at the start of the experiment on the sheet where it says experiment number [GESTURE TO WHERE THEY MUST PUT THEIR NUMBER], then mark next to your choice. **You can only choose one of these options!**

**Game 4a: WTP for weather information (60%-80% probability range)**

This game is similar to one you just played. You have some information that the chances of good weather lie between 60% and 80%. In other words, there could be six black and four white balls in the bag, seven black and three white balls in the bag OR eight black and two white balls in the bag. [DEMONSTRATE THIS]

You will indicate how much you would like to pay for information to know precisely how many black balls (chances of good weather) there are in the bag before you make your choice, in this particular case where the chances lie between 60% and 80%.

Are there any questions?

Ok, let's start. Please write the number we gave you at the start of the experiment on the sheet where it says experiment number [GESTURE TO WHERE THEY MUST PUT THEIR NUMBER].

Indicate (tick) the amount you are willing to pay on the sheet provided.

**Game 4b: Choice after weather information round (60%-80% probability range)**

Again, we have determined who is receiving information before making a livelihood choice. Just like before, if you are among those receiving the information, we are going to hand you an envelope including a picture of a bag with 10 balls, showing you how many black and white balls there are in the bag. Do not reveal this picture to anyone else. If you are not receiving information, you will also receive this envelope but there will be no information inside. Everybody will then make their decisions.

Check the envelope handed to you and use the information inside to help you choose a livelihood option, given the chance of good weather as contained in the information in the envelope. If you have received an empty envelope, it means you did not qualify to receive information in this game and are required to make a choice without information on the precise number of black or white balls in the bag.

Are there any questions? [CHECK TO SEE ALL HAVE UNDERSTOOD]

Please write the number we gave you at the start of the experiment on the sheet where it says experiment number [GESTURE TO WHERE THEY MUST PUT THEIR NUMBER], then mark next to your choice. **You can only choose one of these options!**

**Game 5a: WTP for weather information (50%-90% probability range)**

This game is similar to one you just played. You have some information that the chances of good weather lie between 50% and 90%. In other words, there could be five black and five white balls in the bag, six black and four white balls in the bag, seven black and three white balls in the bag, eight black and two white balls in the bag, OR nine black and one white ball in the bag. [DEMONSTRATE THIS]

You will indicate how much you would like to pay for information to know precisely how many black balls (chances of good weather) there are in the bag before you make your choice, in this particular case where the chances lie between 50% and 90%.

Are there any questions?

Ok, let's start. Please write the number we gave you at the start of the experiment on the sheet where it says experiment number [GESTURE TO WHERE THEY MUST PUT THEIR NUMBER].

Indicate (tick) the amount you are willing to pay on the sheet provided.

**Game 4b: Choice after weather information round (50%-90% probability range)**

Again, we have determined who is receiving information before making a livelihood choice. Just like before, if you are among those receiving the information, we are going to hand you an envelope including a picture of a bag with 10 balls, showing you how many black and white balls there are in the bag. Do not reveal this picture to anyone else. If you are not receiving information, you will also receive this envelope but there will be no information inside. Everybody will then make their decisions.

Check the envelope handed to you and use the information inside to help you choose a livelihood option, given the chance of good weather as contained in the information in the envelope. If you have received an empty envelope, it means you did not qualify to receive information in this game and are required to make a choice without information on the precise number of black or white balls in the bag.

Are there any questions? [CHECK TO SEE ALL HAVE UNDERSTOOD]

Please write the number we gave you at the start of the experiment on the sheet where it says experiment number [GESTURE TO WHERE THEY MUST PUT THEIR NUMBER], then mark next to your choice. **You can only choose one of these options!**

Chapter 5

# 5 Summary of key findings, general conclusions and policy implications, and directions for future research

The essays in this thesis chapters look into barriers and enablers/interventions that have the potential of enhancing adoption of climate change adaptation and sustainable agricultural intensification practices (SAIPs). In this final chapter, a summary of key findings from these studies presented as well as general conclusions and areas identified that can benefit from future research.

## 5.1 Key chapter findings

**Chapter two** assesses the barriers of- and enablers to farm diversification (both livestock and crop enterprises) as an adaptation strategy to climate change in semi-arid areas, and evaluates the implications of this diversification to household food security outcomes. The key Chapter findings are that past exposure to climatic shocks and access to climate information are instrumental in explaining extent of diversification in both livestock and crop farming. These findings are similar to those from Chapter one that climate (weather information) provision is a key success factor to climate change adaptation and sustainable intensification. Further, classical barriers to technology adoption including low education levels for the household head, female headed-households and credit constraints were also found to be binding for farm diversification in the study area.

The study also evaluated the effect of diversification levels and food security in the region. The evidence provided in the chapter show that the higher the extent of farm diversification in a household, the more food secure that household is. Diversification in both livestock and crop farming is associated with high per capita monthly food expenditures and household dietary diversity scores (HDDS). The study finds no evidence that high diversification in either crop or livestock farming relative to the other leads to higher food security outcomes, households highly diversified in both are shown to achieve higher food security outcomes compared to their counterparts.

**Chapter three** set out to test if the emergence of large grain traders in smallholder farmer grain markets in Kenya has an effect on the uptake of sustainable intensification inputs like fertilizer, manure and climate-stress resilient seeds (improved seeds). The study shows that adoption of improved seeds and manure is persistent and once farmers start using these, they continue using them in the future, implying a path dependency in the adoption of these inputs. While the study finds no evidence that large grain sales affect improved seed and manure takeup, there is overwhelming evidence that these sales result in high uptake of inorganic fertilizer.

As indentified in the conceptual framework, the services rendered by these market actors to farmers include provision of inputs on credit, advisory services and mitigation of marketing risks by availing a ready market and stable prices to the farmers. All these are ways which could be driving the observed positive relationship between sales to large gran traders and adoption of fertilizer. The study employed methods that correct for endogeneity in self selection and reverse causality, thus the ability to claim causality with a high degree of confidence on the observed positive relationship. Classical barriers to technology uptake like household head level of schooling and gender, liquidity constraints and accessibility of extension advise are also shown to play a significant role in the adoption of these sustainable intensification inputs, alongside the key explanatory variable, sales to large grain traders.

**Chapter four** sought to understand how climate change-induced uncertainty impacts farming households' decision making on livelihoood choices and technology uptake. The key findings in this chapter show that weather uncertainty leads to sub-optimal choices that decrease a household's welfare outcomes in the face of climate change; the higher the level of weather uncertainty, the low the welfare outcomes from observed choices. The study also establishes that there is a high demand for weather information that reduces this uncertainty, and that provision of weather information enables farmers to make welfare improving choices, even in the presence of climatic shocks like drought. The chapter thus identifies provision of weather information as a key success factor in the effort to enhance adoption of technologies (e.g. improved seeds) that are adaptive to climate change and promote sustainable agricultural intensification.

## 5.2 General conclusions and policy implications

This dissertation identifies new pathways for enhancing adoption of climate change adaptation and sustainable agricultural intensification strategies, as well as provides evidence that pathways established in the literature also work in regions that form part of the studies sites. Chapter 1 shows that availing weather related information to farmers during planting seasons help them in choosing the right technologies given the seasonal weather forecasts. These choices lead to improved household welfare. Chapter 2 further identifies provision of climate change-related crop and livestock management information as key to enhancing take up of improved seed and overall farm diversification. Improved seeds and farm diversification are established risk management practices at farming households, enabling both sustainable agricultural intensification and climate change adaptation. Thus these key findings point to the need for a comprehensive information policy encompassing short and long term weather information and the appropriate response strategies available in both crop and livestock farming enterprises to withstand any stressors associated with the predicted weather outcomes. These include appropriate seed technologies and diversifications in crop and livestock enterprises for creating resilience in the production systems to withstand climatic shocks.

As shown in Chapter 3 of the dissertation, the emergence of large grain traders in smallholder farm markets helps in incentivizing the use of inorganic fertilizer at household level. This provides evidence of a new pathway for policy interventions aimed at enhancing uptake of sustainable agricultural intensification at smallholder farms. Private companies engaged in large grain business can be used as conduits of services like input, credit and extension information provision through public-private partnerships. This could be a cost effective and efficient intervention compared to others like direct input provision by the government that are bedevilled with bureaucracy, moral hazards and corruption. In addition, one large private trader can reach many farmers per interaction and the services are also demand driven, eliminating inefficiencies.

The study also shows that access to land is a key success factor for farmer engagement with these types of market actors. Owners of considerably bigger tracts of land are therefore advantaged to engage with large grain traders, compared to those who own small pieces, most likely due to economies of scale in production and marketing. To make engagements between owners of small farms and large grain traders possible, government can subsidize these actors' costs and act as an insurer for bad debts, which enables them to lend credit to a section of market who are most at risk to default. Such arrangements have been successful elsewhere, for example in provision of index-based livestock insurance (IBLI) in Kenya wher government has partnered with private insurance companies, or the similar index-based weather insurance for crops, which has had mixed fortunes as a potential vehicle for climate change adaptation.

Other key findings point to the need for policies targeted to particular segments of the society to enable populations within these segments access farming risk management strategies. For example, female-headed households are shown throughout the dissertation studies to consistently adopt less technology than male-headed ones. The literature reviewed in these studies paint a picture of female-headed households being stuck in poverty traps characterized by low income earning opportunities, land tenure arrangements skewed against women land ownership, and low ownership of assets, some key for dissemination of information like radios. A policy of credit provision specially targeted for women could make a difference in unravelling these poverty traps.

This could be micro-finance institutions lending to women at discounted rates and subsidized by the government or development partners, shown to improve women empowerment elsewhere. Studies elsewhere have also shown higher impact of projects where the recipient pool is made up of women, for example livestock disbursed to females to spur female ownership of the asset.

On the other hand, investments in education of the rural population results in higher adaptation take up. Outside farm diversification, this is also critical for other adaptation strategies not addressed in the study like migration where educated migrants are shown to earn more and also send higher remittances home, given the high income opportunities they have in off-farm employment. Thus for a broader adaptive capacity of the rural population, especially in Namibia where rural education levels are shown to be very low, policies geared towards access to education by the rural poor needs prioritizing.

### 5.3 Future research

In **Chapter two**, the study only touches on farm diversification (livestock and crop) as a strategy to coping with climate change. As earlier stated, Namibia is projected to be highly impacted by climate change and there has been a steady migration of people in search of non-farm activities. How does diversification of households in the region into all three activities i.e. crop, livestock and non-farm, affect welfare of migrants (e.g. through access to non-farm incomes in non-farm sectors) and non-migrants (through loss of extra farm labour and access to remittances from the emigrating household members)? With access to a rich household and indivial panel data, this would be an interesting area of research. Accessing such data is however both time consuming and expensive, but might be necessary as a government undertaking for future policy making. This is especially important for Namibia where such datasets are non-existent and which faces a significant challenge posed by the changing climate.

I also acknowledge areas of limitation in **Chapter three** that could benefit from further research. First, my definition of large grain traders (LGTs) solely relies on farmers recall and their ability to identify the type of traders that they sold their grain to. Future studies on this aspect may need to find a more robust way of identifying these market actors. Secondly, the study relies on few observations for households selling their grain to LGTs across the panel, given that these types of market traders are still making incursions in the small-holder grain markets. Thus, while the results from our analysis offer useful insights especially in this understudied area and given the potential important role that LGT can play in farm production decisions, the low numbers of LGTs used in the analysis may lead to some measurement errors.

Lastly, To evaluate the role of weather information in farming decision making in **Chapter four**, the study utilized a framed field experiment. The framing of the weather uncertainty scenarios and introducing the possibility of reducing this uncertainty through provision of weather information gave important insights on demand for this information, and choices made after accessing the information. It would be interesting to assess how these choices play out in the real world. An area of further research to this end could be in the form of a randomized control trial (RCT) intervention where weather information is disseminated to treatment groups then real farming choices are observed. Further, while the study assessed how availing weather information can help farmers make better farming decisions, the study did not go further to look into what would happen if the provided information turned out to be incorrect, as it so happens in most cases in sub-Saharan Africa where weather prediction is usually not precise. Does this lead to loss of trust and future non-use of weather information coming from meteorological weather stations? This is an empirical question that could be interesting to explore to explain why farmers do not use weather information even in countries where this is often provided.