CLIMATE-CHANGE ADAPTATION AMONG SMALLHOLDER FARMERS IN ZAMBIA

by

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DECLARATION OF OWN WORKS

I, Obrian Ndhlovu, declare that this thesis is my own unaided work, both in concept and execution, and that apart from the normal guidance from my supervisor, I have received no assistance except where appropriately acknowledged in the text. I further declare that neither the substance nor any part of this thesis has been in the past, or is being, or is to be submitted for a degree at this University, or any other university.

Signed by candidate

30th March, 2023
date

DEDICATION

- to grandma Hillah S. N. Nkosi, my wife Nancy,

my daughters Sibusisiwe and Nina,

and my sons Thabani and Melusi.

- to the memory of Prof. Venkatesh Seshamani

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My wife and children had to bear with my long absence from home. To you, words could never be sufficient to say thank you.

ABSTRACT

In Zambia, climate variability has resulted in declining and more erratic rainfall. Soil fertility has also declined, mainly from over use and use of environmentally unfriendly farming methods. These factors have contributed to declining farm productivity and revenue, leading to increased poverty levels in rural areas and undermining efforts to achieve sustainable development goals on poverty eradication and ending hunger. The country has been promoting adaptation practices such as conservation farming, crop diversification and irrigation in order to help smallholder farmers adapt to the climate. Despite these efforts, observation suggests suboptimal levels of adaptation.

In three substantive chapters, this thesis investigates the strategies smallholder farmers use to adapt to variability in rainfall, the impact of policy reforms on adoption of sustainable farming practices, and whether farmers find these practices beneficial. The thesis has the potential to inform policy on climate adaptation, the effectiveness of input support programme reforms on influencing farmer behaviour and the relevance of new climate smart agricultural technologies in the climate adaptation agenda. The thesis also proposes measures of household variables, such as education and gender, that capture information beyond the head of household as is common in the literature.

Chapter 2 assesses farmers' responses to variability in rainfall and investigates drivers behind adaptation strategy choice, including the adoption of conservation farming and other climate adaptation strategies such as crop diversification and irrigation. The seemingly unrelated regression estimation is used to investigate the adoption of farming practices while the ordered Probit and Tobit models are used to analyse the magnitude and intensity of adoption, respectively. The chapter contributes to the literature on climate adaptation by analysing adoption in a more broader sense by looking at the diversity and intensity of adoption, employing methods that are robust to interrelationships among adaptation strategies, the use of unique data combining quantitative and qualitative data, which enables the chapter to provide context to the findings.

The results show that the level of adoption of conservation farming, crop diversification and irrigation remains low. There is also evidence of adoption reversal. The major challenges to adoption include low level of access to complementing practices such as use of herbicides, the practice of open grazing, the entrenched culture of maize monocropping, which is exacerbated by general lack of structured input and output markets for alternative crops. This calls for the

scaling up of agricultural extension services to support skills and knowledge acquisition for the adoption of new farming practices, including the use of herbicides.

Chapter 3 evaluates the impact of input subsidy programme reforms on the adoption of crop diversification and rotation practices among smallholder farmers. The difference-in-differences approach in combination with propensity weighting/matching and endogenous treatment approach is employed. The findings have the potential to inform the ongoing reforms in the agricultural subsidy programme. While the analysis of agricultural input subsidy programme pursue primary objectives such as the impact on fertiliser use, crop yield and hunger or poverty, this chapter analyses the impact of such programmes in facilitating climate adaptation, which may be considered a secondary objective and not well understood. The chapter also employs a unique data structure that permits the identification of treatment effect.

The results show that the opening up of the input subsidy to multiple crops had a significant positive impact on household crop diversification. The electronic voucher system, although having a positive impact on crop diversification and crop rotation, has been hampered by the general inertia in the private markets to provide certified inputs of other crops. In addition, the lack of assured markets for outputs of other crops compared to maize has worked against efforts to stimulate crop diversification and rotation. These results suggest that reforms to the subsidy programme must be complemented by parallel reforms in other aspects of agriculture, such as extension services and agricultural markets, if they are to be effective in catalysing or facilitating adaptation to rainfall variability.

Chapter 4 uses plot level data to evaluate the effect of conservation farming on crop yields and downside risk measured using the skewness based measure. The chapter uses the multinomial endogenous treatment effects models to analyse the impact on crop yield and climate-resilience, respectively. The chapter contributes to literature by employing methods that account for the endogenous household level decision to assign CF practices on different crop plots and has the potential to inform the ongoing drive to promote climate adaptation among smallholder farmers.

Plot level evidence shows that crops to which some components of conservation farming are applied tend to have higher yields when rainfall is low. Results also show that crops of farmers who adopt and implement some components of conservation farming are also more likely to survive. These results call for the promotion of the full adoption of conservation farming and other complementing technologies, especially in low rainfall agro-ecological zones, where its impact will be most appreciated.

Brief Contents

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LIST OF ACRONYMS

AEO	Agricultural Extension Officer
AEZ	Agro-Ecological Zone
ATE	Average Treatment Effect
CAC	Camp Agricultural Committee
CC	Climate change
CD	Crop Diversification
CDF	Cumulative Density Function
CEO	Camp Extension Officer
CF	Conservation Farming
CFU	Conservation Farming Unit
CHIRPS	Climate Hazards group Infrared Precipitation with Stations
CR	Crop Rotation
CSA	Climate Smart Agriculture
CSO	Central Statistical Office
DACO	District Agriculture Co-ordinator
DiD	Difference in Differences
FAO	UN Food and Agriculture Organisation
FD	FISP Dependence
FISP	Farmer Input Support Programme
FRA	Food Reserve Agency
IAPRI	Indaba Agricultural Policy Research Institute
IPCC	Inter-governmental Panel on Climate change
IPWRA	Inverse Probability Weighting with Regression Adjustment
IV	Instrumental Variables
MFL	Ministry of Fisheries and Livestock
MoA	Ministry of Agriculture
MT	Minimum Tillage
MTENR	Ministry of Tourism, Environment and Natural Resources
NNM	Nearest Neighbour Matching
PDF	Probability Density Function
PSM	Propensity Score Matching

RALS	Rural Agricultural Livelihood Surveys
RD	Regression Discontinuity
SC	Soil Cover
SDG	Sustainable Development Goals
SEA	Standard Enumeration Area
SID	Simpson Index of Diversification
SUR	Seemingly Unrelated Regressions
ZMD	Zambia Meteorological Department

Part I

THE PROLOGUE

CHAPTER 1

INTRODUCING THE THESIS

1.1 Introduction

Climate change has become a global topic, driving today's global development agenda. The industrialisation of the world is lauded for creating innovation, employment, and immeasurable global value. However, its impact on the environment is slowly showing through climate change, leading to an increase in the frequency of extremes in climatic variables, such as storms and droughts, global warming, rising sea levels, and the disruption of ecosystems (Lal et al., 2001). At the same time, soil fertility has also deteriorated, mainly from over-use and the use of farming methods that are not friendly to the environment, such as traditional intensive soil tillage, burning of crop residue, and the general lack of soil cover during dry seasons (Arslan et al., 2014; Habanyati et al., 2018). Prolonged droughts have permitted the depletion of the vegetation needed to protect the soil and enhance its quality, while excessive rains have exacerbated the problems of soil erosion. This has contributed to declining farm productivity and revenue (Baudron et al., 2007; Di Falco and Veronesi, 2013), leading to increased poverty levels, especially among rural communities of developing countries. In Zambia, for instance, the UNDP (McSweeney et al., 2012) reported that the annual temperature has gone up by as much as 1.3°C in the last half century while the rains have decreased both in quantity and duration.

Although climate change is a global problem, most predictions show that the effects will be disproportionally felt by the poor in the 'third world' (Altieri and Koohafkan, 2008; Lal et al., 2001). In the first place, populations in developing countries are resource constrained and therefore unable to adequately adapt and cope with the severe effects of climatic variability, especially rainfall extremity (Fussel and Klein, 2006; Smit and Pilifosova, 2001). Secondly, rain-fed agriculture remains a source of livelihood for the majority of rural populations in developing countries. As such, changes in climatic variables, such as rainfall and heat, are likely to have a big impact on the welfare of the already poor, undermining efforts to end poverty and hunger.

The intergovernmental panel on climate change (IPCC) (Altieri and Koohafkan, 2008) projected that climate change could cause yields from rain-fed agriculture to fall to as low as half of their current levels due to stresses such as water shortages, aridity, and heat. In this regard, the UNDP has recognised climate change as a new threat to the realisation of sustainable development goals (SDGs). For instance, the achievement of SDG 1 on poverty eradication[1] and SDG 2 on ending hunger and achieving food security[2] are being hampered by the consequences of climate change, such as droughts and biodiversity loss.

The world is now looking to climate-resilient agricultural systems, especially among smallholder farmers of developing countries, as a climate-change adaptation measure to help vulnerable people cope with the changing environments in which they are living (WFP, 2009). At the continental level, the African Union Agenda 2063 sets the tone for Africa's response to climate change, among many other pressing needs.[3] The agenda lists seven (7) aspirations to guide the continent's 50-year agenda. Climate change is recognised in the agenda and factored into the development aspiration. In particular, the continent seeks to foster environmentally sustainable and climate-resilient communities through promoting investment in sustainable and climate-resilient production systems such as conservation farming (AUC, 2015).

At a country level, Zambia has developed a climate change response strategy whose aim is to support and facilitate a coordinated response to climate change issues in the country (MTENR, 2010). For agriculture, the strategy envisions the development of a sustainable land use system to enhance agricultural production and ensure food security through the increased support for meteorological department's early warning system, encourage crop diversification including the cultivation and consumption of indigenous and drought tolerant food crops, provision of farm inputs like inorganic fertiliser. Other strategies include the promotion of improved soil and land management practices such as conservation farming and agroforestry, and enhanced investment in water harvesting and storage infrastructure to support irrigation, among other strategies. These strategies are intended to help increase resilience to variability in climatic variables, especially rainfall (Ngoma et al., 2017; Ngombe et al., 2014; Pretty and Bharucha, 2014) as well as improve soil quality and crop yield (Arslan et al., 2014; Zulu-Mbata et al., 2016). For instance, it is argued that conservation farming is the best on-farm practical solution for minimising the effects of erratic rainfall and droughts (CFU, 2007, 2012) and it is being promoted as a practice that would help improve soil quality, yields, and resilience to rainfall variability (Pretty and Bharucha, 2014; Zulu-Mbata et al., 2016).

Zambia has strengthened efforts to promote the adoption of these climate-smart agricultural practices in order to build climate resilience, especially among smallholder farmers. A number of partners have also cooperated in promoting the adoption of conservation farming, irrigation schemes, crop diversification, and crop insurance by providing subsidised complementing inputs

[1] SDG 1 is to "End poverty in all its forms everywhere".

[2] SDG 2 is to "End hunger, achieve food security and improved nutrition and promote sustainable agriculture".

[3] The African Union Agenda 2063 is Africa's strategic framework and includes inclusive and sustainable development among other goals for the continent.

and services (Baudron et al., 2007; Zulu-Mbata et al., 2016). In addition, the government has reformed the farmer input support programme (FISP) by including other crops, such as sorghum, cotton, and groundnuts, and most recently by the introduction of the electronic voucher input delivery system (MoA, 2012). FISP provides subsidised inputs to *vulnerable but viable smallholder farmers* but had previously provided inputs for maize only (Mason et al., 2013).

Despite efforts to promote climate adaptation among smallholder farmers and the perceived benefits of these practices in mitigating the adverse effects of variability in climatic variables, the level of adoption of these practices among smallholder farmers remain low (Arslan et al., 2015; Baudron et al., 2007; Grabowski et al., 2014; Kassam et al., 2019; Zulu-Mbata et al., 2016). There are also observed cases of dis-adoption or abandonment, where farmers who initially adopted a new farming practice abandon the practice and revert back to traditional methods (Habanyati et al., 2018; Michler et al., 2019; Pedzisa et al., 2015a; Teklewold et al., 2013a).

The slow adoption and observed dis-adoption of climate-smart farming practices raises questions about the viability of these practices to mitigate negative effects of rainfall variability and their appropriateness to smallholder farmers. How are farmers adapting to increased rainfall variability? What factors are driving adoption of climate-smart farming practices? What has been the role of policy? Does conservation farming increase resilience to rainfall shocks from the farmers' perspective? The available literature is not conclusive on these questions and, in some cases, there have been mixed results. There are gaps in the information on the drivers of and barriers to climate adaptation. Although there have been attempts to use government policy to influence adaptation, the impacts of these have not been adequately evaluated. The extent to which some of the adaptation strategies, such as conservation farming, are helping farmers also remain unresolved especially at the country level. The above questions can be categorised into three thematic areas: (1) understanding what and how farmers choose to adopt; (2) how policy can be used to influence adaptation and (3) whether the chosen strategies do add value.

Studies on the drivers of adoption, non-adoption and dis-adoption or abandonment are inconclusive but point to levels of education, availability of enabling environment such as markets and appropriate technology, and land tenure systems (Grabowski et al., 2014; Kassie et al., 2013; Pedzisa et al., 2015a; Zulu-Mbata et al., 2016). Studies looking at the impact of agricultural input support programmes have found significant impacts on primary objectives such as input use and crop yield (Asfaw et al., 2017; Carter et al., 2014; Chibwana et al., 2014; Jayne and Rashid, 2013; Xu et al., 2009). However, the impact of these programmes and reforms on the adoption of climate-resilient agricultural technologies remain inconclusive, with some showing agricultural support programmes significantly influencing the adoption of climate-smart agricultural practices (Kankwamba et al., 2018; Koppmair et al., 2017) while others find no significant effects (Jayne et al., 2018b).

The impact of adopted practices on smallholder welfare, including crop yield and resilience to rainfall variability has also resulted in mixed results. For instance, the adoption of conservation farming was found to be beneficial mostly in the long-run (Abdulai, 2016; Abdulai and Huffman, 2014; Busari et al., 2015; Michler et al., 2019; Montt and Luu, 2018). Other studies however, find weak results or attribute the observed impacts to increased input use such as increased usage of fertiliser and herbicides that is associated with new farming practices such as conservation farming (Arslan et al., 2015; Michler et al., 2019; Tessema et al., 2015). The current literature lacks conclusive evidence on whether these climate-smart farming practices do improve resilience to rainfall variability. While lessons can be drawn from global, continental and regional studies, these may not be very informative in crafting specific action points especially in the agricultural sector which is influenced by local contexts such as the microclimate, farming systems and cultures (Baudron et al., 2007; Hobbs et al., 2008; Lee, 2005)

This thesis will contribute to the literature on climate-change adaptation or simply climate adaptation by investigating smallholder farmers' options in the face of increased variability in climatic variables with specific reference to Zambia. The thesis attempts to address the following broad questions:

- What are the drivers of different adaptation strategies used by smallholder farmers?
- What has been the impact of policy reforms on smallholder farmers' adoption of climate-smart and sustainable farming practices? and
- Do smallholder farmers find these climate-smart agricultural practices, with particular reference to conservation farming, beneficial?

The thesis will address these questions in three analytical chapters presented in Part II as chapters 2, 3 and 4. In particular, chapter 2 examines factors favouring or inhibiting climate adaptation among smallholder farmers. The chapter particularly examines the extent to which extension services and exposure to climate hazards can drive the adoption of climate adaptation farming practices. Chapter 3 then looks at the impact of the farmer subsidy programme reforms on the adoption of new farming technology. In particular, this chapter evaluates the impact of the introduction of multiple crops in the farmer input support programme, and the electronic voucher delivery system, on the yield of supported crops, the degree of household-level crop diversification, and the degree to which farmers adopt crop rotation. Finally, chapter 4 looks at the effectiveness of conservation farming in increasing crop yield and resilience to adverse weather conditions.

1.1.1 Broad Objectives

The analytical chapters (in Part II) will be guided by the following broad objectives, with sub-objectives also shown;

- to determine factors that drive the adoption of different CC adaptation strategies among smallholder farmers.

  - to document strategies that smallholder farmers are employing to mitigate the impact of CC.
  - to investigate determinants of the decision to adapt to CC.
  - to investigate determinants of the choice of different adaptation strategies by smallholder farmers.

- to determine the impact of the farmer input support programme reforms on smallholder farmers' adoption of climate-smart and sustainable farming practices.
  - To estimate the impact of FISP reforms on the yield of maize.
  - To estimate the impact of FISP reforms on the yield of newly introduced crops with specific reference to groundnuts.
  - To estimate the impact of FISP reforms on the degree of crop diversification.
  - To estimate the impact of FISP reforms on the adoption of crop rotation.

- to examine the impact of the adoption of conservation farming on smallholder farmers' performance in the context of rainfall variability.
  - to determine the impact of CF on crop yield.
  - to determine the impact of CF in reducing the downside risk on crop yield.

1.1.2 Relevance of the Thesis

The thesis will inform policy on the state of climate-change adaptation among smallholder farmers, factors that influence adaptation, and how policy can be used to influence adaptation. The thesis will also provide information on the relevance of conservation farming as a climate adaptation strategy, with the potential to influence both policy and farmers' perception of the practice.

The thesis also contributes to the literature on climate adaptation using three novel approaches. First, the thesis employs a rich and unique combination of datasets which include a nationally representative survey of smallholder farmers, satellite rainfall data, and qualitative data from in-depth interviews with agricultural extension workers. The quantitative data allow controlling for a number of factors that influence farmers' behaviour and crop performance, while the qualitative data provides context and an explanation of the quantitative results.

Secondly, the satellite rainfall data allows the estimation of objectively measured rainfall variables, such as extreme rainfall. Objectively measured rainfall outcomes are important in smallholder studies because rainfall not only affects crop performance, but also influences farmer behaviour towards climate adaptation.

Thirdly, the thesis introduces a number of innovations to the measurement of variables from which future research can build on. For instance, the thesis suggests the incorporation of broader measures of gender and education in a household, as well as the farmers' dependence on subsidies, which might influence their responsiveness to policy reforms.

The thesis is organised in three parts. Part I as well as giving a general introduction, discusses the agriculture and climate of Zambia (section 1.2), and a broad discussion of data sources (section 1.3). Part II contains the three analytical chapters at the core of this thesis as Chapters 2, 3 and 4. Part III draws overall conclusion and implications for policy.

1.2 Background

This section provides some overall background which gives an overview of agriculture (1.2.1) and the agro-climate in Zambia (1.2.2).

1.2.1 Agriculture in Zambia

Zambia covers a land area of approximately 75 million hectares. About 58% of the land is considered arable, although a significant portion of it lies in the semi-arid regions of the Central, Eastern and Southern provinces (MoA and MFL, 2016; MTENR, 2010). Agriculture remains a key sector of the Zambian economy. The 2015 Living Conditions Monitoring Survey (CSO, 2016a) shows that the sub-sectors of agriculture, forestry and fisheries account for 58.7% of employed persons country wide and 86.9% among the rural population, most of whom are self-employed on smallholder family farms. The Central Statistical Office (CSO, 2016b, 2017) estimates that there are about 1.47 million smallholder households in the country. Of these, about 71% at the time of the survey were cultivating less than 2 hectares of land, 23% cultivating 2-5 hectares, and only 6.3% were cultivating between 5 and 20 hectares (CSO, 2016b, 2017).[4]

Maize is the country's staple crop and the one most widely grown. For instance, post-harvest surveys show that close to 90% of smallholder households grow maize, although the percentage is slightly lower in the northern region where cassava is also widely grown (CSO, 2014, 2016b, 2017). Other important crops include groundnuts, sorghum, millet, and soybeans.

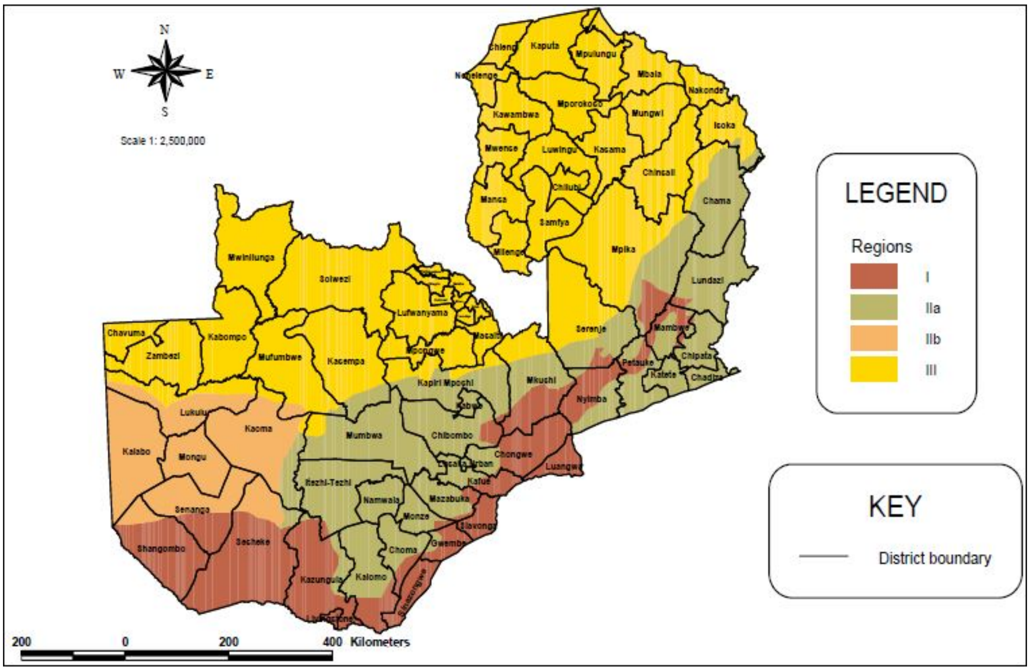
1.2.2 Agro-Climate of Zambia

The agro-climate of Zambia varies considerably. The annual rainfall varies from more than 1200mm in the northern regions of the country to less than 700mm in the southern regions (Jain, 2007; Libanda and Ngonga, 2018). The variations in climatic variables, mainly rainfall, partition the country into three agro-ecological zones (AEZ) (Andersson and D'Souza, 2014; Arslan et al., 2014; Jain, 2007), as shown in figure 1.1.

Region I covers approximately 12% of the country's land area and lies in the southern part of the country (MoA and MFL, 2016). The region was considered the grain basket of Zambia but has been hard hit by unpredictable and poorly distributed rains in recent years (Jain, 2007). The region receives an average annual rainfall of less than 800mm and is prone to frequent

[4] There is no universal agreement on the threshold of land area of a smallholder, although a threshold of 2 hectares is often used (Feliciano, 2019). In Zambia, smallholder farmers are defined as farmers cultivating less than 20 hectares (Haggblade and Tembo, 2003; Mason et al., 2013; Sitko and Jayne, 2014).

Figure 1.1: Zambia Agro-Ecological Zones



Source: MoA and MFL (2016)

droughts or dry spells (MoA and MFL, 2016). Consequently, its potential for crop production is on the decline (Jain, 2007).

Region II lies in the country's midlands, covers approximately 42% of the country's land area, and receives between 800mm and 1000mm of rainfall annually (MoA and MFL, 2016). The region is subdivided into region IIa in the east and IIb in the west, with the latter suitable for rice production as well as other crops. Region III lies in the northern part of the country, covering approximately 46% of the country. This is a high rainfall region, receiving an average annual rainfall in excess of 1000mm.

Projections into the future indicate that average rainfall will continue to decline over much of Zambia. The country is projected to have an increased number of consecutive dry days, which has the potential to have a negative impact on the performance of the agricultural sector (Libanda, 2020; Libanda and Ngonga, 2018).

1.3 Broad overview of Methods and Data

The thesis employs a mixed-methods approach which combines econometric and qualitative methods that vary from chapter to chapter. In the analysis of adaptation, the econometric methods employed include the multi-variable probit models based on Zellner's (1962, 1963) seemingly unrelated regressions. Ordered probit and bounded tobit models are also used to analyse partial adoptions, in which farming practices are adopted sequentially or applied on a successively increasing proportion of land.

The analysis of the impact of input subsidy reforms on the adoption of climate-related farming practices employs the *Neyman-Rubin* model of causal inference (Imbens and Wooldridge, 2009; Rosenbaum and Rubin, 1983; Sekhon, 2010). This builds on the structure of the data, which provide observations before and after the reform, allowing the use of treatment effect models. The thesis deals with the non-random assignment to treatment by using a combination of difference-in-differences and propensity weighting and matching as well as endogenous treatment approaches based on Deb and Trivedi (2006b), Fredriksson and Oliveira (2019), and Stuart et al. (2014). To evaluate the effectiveness of conservation farming, the thesis employs the multinomial endogenous treatment effects model (METEM) based on Deb and Trivedi (2006a,b). The METEM has the advantage of being robust to the endogenous application of CF on crops or field plots.

The main data comes from two waves of the Rural Agricultural Livelihoods Surveys (RALS) (CSO, 2015), discussed below (subsection 1.3.1). The main data are supplemented with primary key informant interviews data, described in subsection 1.3.2, and high resolution satellite rainfall data described in subsection 1.3.3. Each analytical chapter will be based on a selected subset of this dataset. Quantitative data are analysed mainly using Stata. In addition, Tableau[5] is used to generate geographical maps while Nvivo[6] is used to analyse qualitative data.

1.3.1 The Rural Agricultural Livelihood Survey data

The Central Statistical Office (CSO), together with Indaba Agricultural Policy Research Institute (IAPRI) in Lusaka and the Ministry of Agriculture (MoA), conducts annual crop forecasting and post-harvest surveys, which collect crop information at a household level on area planted, input use, levels of output, and sales (Mason et al., 2013). These surveys were complemented by Supplemental Surveys at regular intervals (2001, 2004 and 2008), based on the 2000 Census sampling frame, which provide more detailed information on rural livelihoods, including crop production and sales, off-farm activities, other sources of income, and ownership of farming assets (Arslan et al., 2015; IAPRI, 2016; Mason et al., 2013). The Rural Agricultural Livelihood Surveys (RALS) are a new successor series of panel surveys based on the 2010 Census sampling frame. So far, three rounds of RALS have been conducted (2012, 2015, 2019), although data from the third round are not yet publicly available.

A multistage sampling design was used in the first round in 2012. A total of 476 standard enumeration areas (SEAs) were sampled with probability proportional to their size, using the 2010 Census as the sampling frame. In the 2010 Census of Population and Housing, the country was divided into 25,207 SEAs (CSO, 2013). The size of a SEA is measured by the number of households located within it. Stratified random sampling was then used to sample eligible

5 Tableau version 10.4. Tableau Software. Tableau is useful for working with geocoded data and is able to generate interactive geographical visualisations.

6 Nvivo version 12 by QSR International Pty Ltd. Nvivo is helpful for coding, retrieving and analysis qualitative data.

households within each SEA, with strata based on farm size. The strata were smallholder farmers cultivating less than 2 *ha* of land (category A farmers), cultivating $2-5$ *ha* (category B farmers) and cultivating $5-20$ *ha* (category C farmers) (CSO, 2015).[7] The three categories were allocated 5, 5, and 10 respondents respectively to yield 20 respondents in each SEA. Reallocation was permitted if the number of households in a particular category fell below the required number. Farmers cultivating more than 20 *ha* were excluded from the sample.

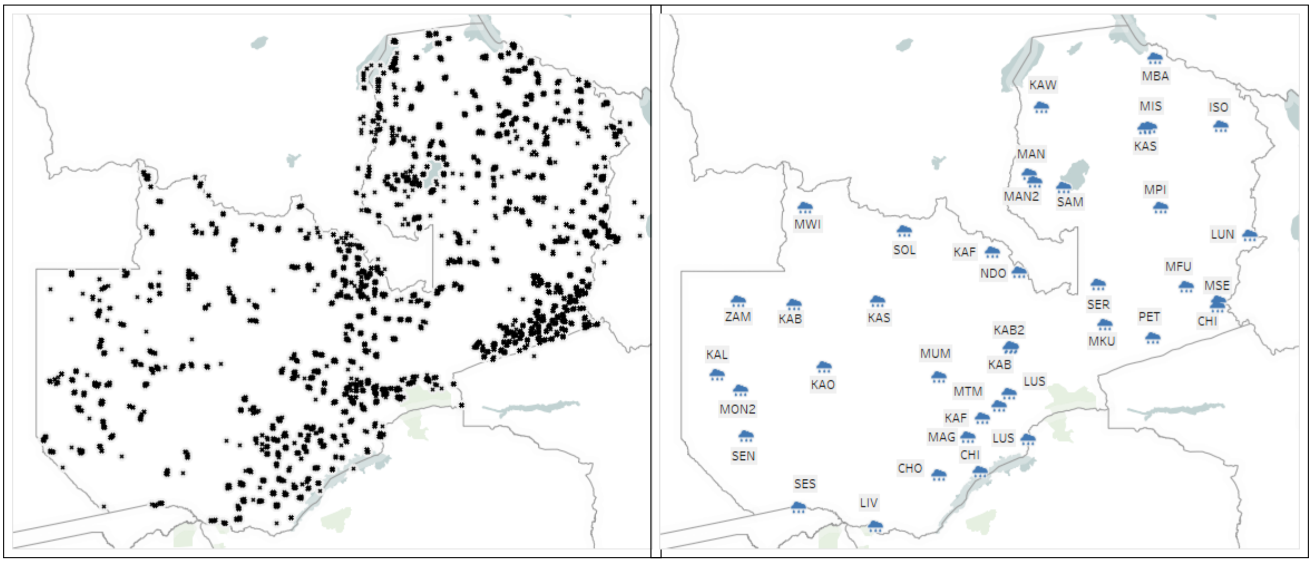
The 2012 round covered 442 SEAs across the ten (10) provinces of Zambia and 8,839 households were enumerated (IAPRI, 2016). The second round, in 2015, followed the same households interviewed in the 2012 round. A total of 34 more SEAs were added (17, 9, and 8 in the Eastern, Lusaka, and Muchinga provinces, respectively), adding 680 households. After accounting for attrition, a total of 7934 households were enumerated in 2015. This gives an unbalanced two-wave panel of 16773 household-level observations as shown in table 1.1.

Table 1.1: Sample sizes from the two waves

		year		
		2012	2015	Total
Panel	No	1585	680	2265
	Yes	7254	7254	14508
	Total	8,839	7934	16773

The data are geo-coded, allowing linkage with other data such as geo-coded satellite rainfall data. The geographical locations of the respondents are shown in figure 1.2a.

Figure 1.2: Geo-location of sampled farmers and Weather stations



(a) Geo-locations of RALS respondents (b) Geo-locations of ZMD Weather stations

The figure shows that the respondents were spread fairly evenly across the country with some visible concentrations in what seem to be high population density centres. The data have

7 Smallholder farmers cultivate less than 20 hectares of land. *See* note 4 on page 8.

modules on demographics; farmland ownership and use; crop production and sales; acquisition of fertiliser and seed; rural loans and credit; livestock, poultry and fish farming; household assets and farming implements; off-farm income and remittances; access to agricultural extension services and adoption/employment of various farming techniques.

1.3.2 Key informant interviews data

Primary in-depth interviews were conducted with agricultural extension workers in two farming districts in Zambia. The qualitative approach solicited detailed information on the available supportive framework for climate-change adaptation, as well as the challenges and opportunities that each adaptation strategy presents. A multi-stage sampling approach was used. First, two farming districts were selected purposefully to represent the two farming regions of the country: Chisamba representing the medium-rainfall region in the central region and Monze representing the low-rainfall region in the southern region.

Chisamba is one of the new districts created out of Chibombo district in 2013,[8] while Monze was an older district. Both districts are mainly agricultural and are two of the few districts with food reserve agency (FRA) grain silos. In addition, Chisamba is home to the Mwomboshi irrigation scheme being developed under the Irrigation Development and Support Project (IDSP) supported by the World Bank (WB, 2011), and Monze was part of an extensive case study by Baudron et al. (2007) on the adoption of conservation farming in the southern province.

For agricultural purposes, districts in Zambia are divided into Agricultural Blocks manned by Block Extension Officers (BEOs). Agricultural blocks are further divided into Agricultural Camps, manned by Camp Extension Officers (CEOs). The rest of the chapter will refer to both BEOs and CEOs as Agricultural Extension Officers (AEO). The role of AEOs, as defined in the Agricultural Diary for Extension Officers (ADEOs) (MoA, 2019), is to provide extension services in order to facilitate the dissemination of information and technologies for improved agriculture at the camp level. AEOs have three key results areas: the training of farmers, the provision of technical support to farmers, and performance management to monitor and evaluate agricultural performance in the AEOs' catchment areas.

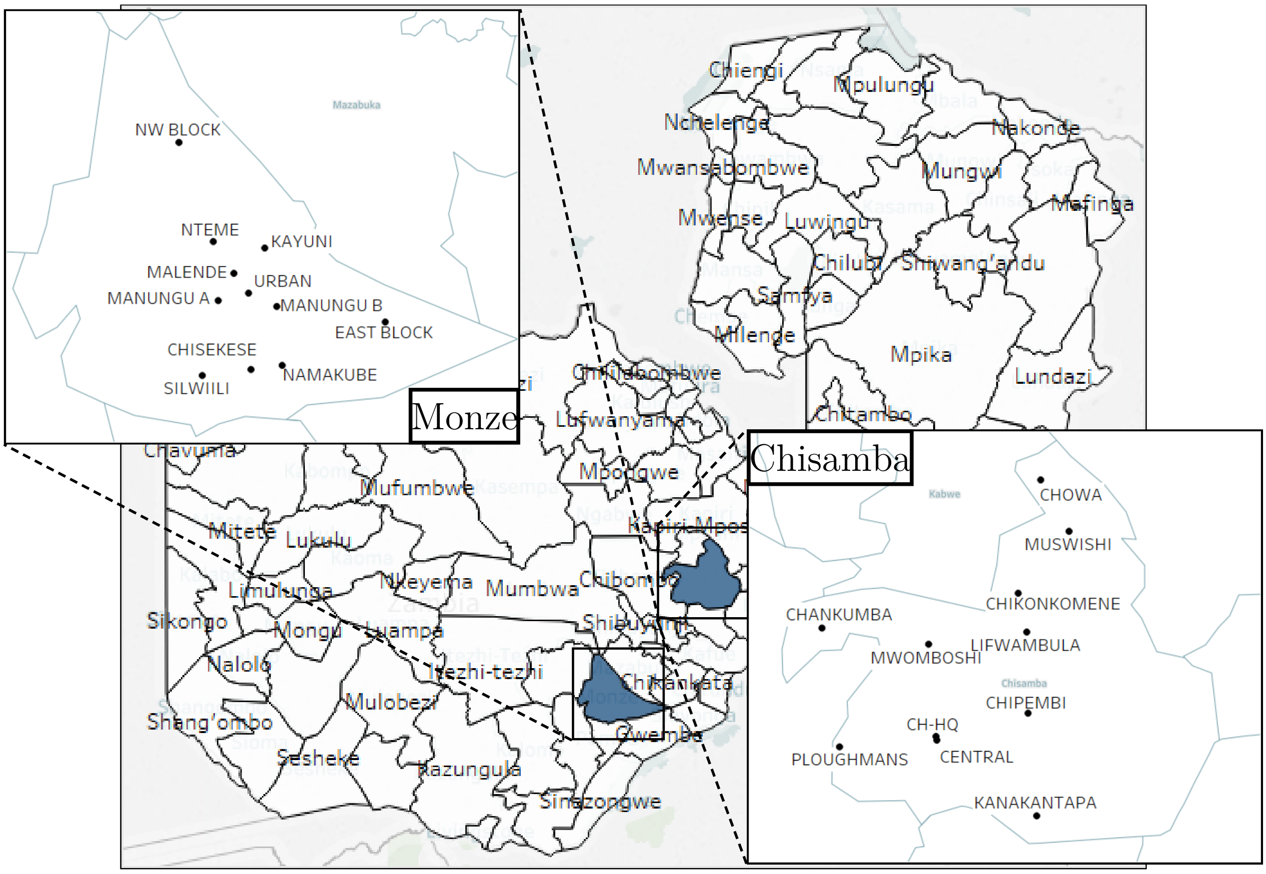
AEOs are in privileged positions and have the expertise to understand the challenges and opportunities that farmers are faced with. They possess expert knowledge on agriculture, which smallholder farmers in particular would lack. This study interviewed AEOs as key informants on climate adaptation among smallholder farmers. The interviewees were selected the help of the District Agriculture Coordinators' (DACO) offices. The offices have detailed lists of AEOs working in the district.

At the time of the interviews, Chisamba had 16 AEOs and Monze had 39. In Chisamba, while there are 16 AEOs, only 10 were available during the interview window and these were all interviewed between the 17th and 20th of December, 2019. In Monze, the list was narrowed

[8] Chisamba district was created out of Chibombo district in 2013 by Statutory Instrument No.49 of 2013.

down by excluding AEOs who had not completed 5 years in their positions. Eleven AEOs were selected using a systematic sampling method by picking every other name on the revised list. These were interviewed between the 23rd and 25th of December, 2019. In addition, one officer from the DACO's office in each of the two districts was interviewed. Figure 1.3 shows the geographical locations of the key informants within the two districts.

Figure 1.3: Geo-location of Key Informants



The map in figure 1.3 does not show the catchment area of each camp as this was not available at the time of the interviews. Nonetheless, the map is still informative on the spatial distribution of the informants interviewed in the two districts and does show a good geographical spread. This is important to ensure that, analytically, the responses cover all possible scenarios in the districts.

The number of respondents is also more than sufficient to obtain both saturation and redundancy as defined in Cleary et al. (2014) and Trotter (2012). That is, all the questions were extensively addressed and more respondents were not likely to bring any new information. The procedure and tools for the interviews are detailed in appendix A. A structured key-informant interview guide was used to solicit information on farmers' perceptions of climate change, the climate adaptation support framework available to help farmers adapt to increased rainfall variability, and information on the adoption of conservation farming and irrigation. Conservation farming and irrigation are two strategies being promoted for climate adaptation.

1.3.3 Rainfall data

Rainfall data are available from two sources: the station-based data from the Zambia Meteorological Department (ZMD) and satellite data from the Climate Hazards group Infrared Precipitation with Stations (CHIRPS). The Zambia Meteorological Department operates forty (40) weather stations spread across the country. See figure 1.2b on page 11 for geographical locations of these stations. The stations provide data on climate variables including rainfall. The data are available on a monthly basis for each weather station. Station based data have the advantage of capturing actual rainfall activity. However, the major weakness, as noted by Hughes (2006), is the sparseness and increasing number of missing observations. This is true for the ZMD data, which only has 40 stations countrywide, with missing data noticeable especially in more recent years, as shown in table 1.2. The table shows the number of stations that reported on all days of the month in a year and in the 6 months from October to March.

Table 1.2: Number of stations with complete daily readings

	2010	2011	2012	2013	2014	2015
All 12 months	21	21	13	4	5	3
October to March*	25	24	22	9	9	6

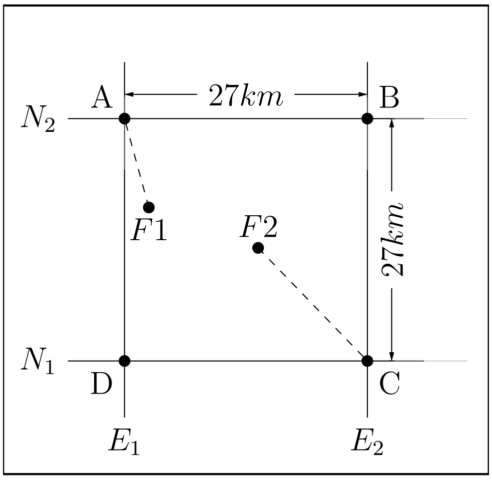
* October to March is the rainy season in Zambia.

As noted by Hughes (2006), station-based rainfall observations are not only sparse to begin with, but there is also a high and increasing level of missing data. This is particularly true with the ZMD data which shows an increasing number of missing observations, as shown in table 1.2. For instance, of the 40 stations, only five (5) or fewer had complete daily readings for each month and fewer than ten (10) in the period October to March in the 2013-2015 farming seasons.

The CHIRPS uses the tropical rainfall measuring mission multi-satellite precipitation analysis to calibrate cold cloud duration rainfall estimates (Funk et al., 2015). Daily data are available at $0.25° \times 0.25°$ (approximately $27.75km \times 27.75km$) spatial resolution. This has the advantage of being complete and of high resolution, providing rainfall estimates at points closest to individual farmers. However, it has been observed that satellite technologies tend to underestimate actual rainfall (Hughes, 2006). Although examining the validity of satellite data is beyond the scope of this chapter, I ran the Pearson correlation between satellite and station data to assess the level of correlation. I merged the two rainfall data sets by linking each station to the nearest satellite point and aligning the year and month of data for available station observations. The Pearson correlation coefficient is run between the satellite and station rainfall readings and finds a correlation coefficient of $r = 0.8973$.

Based on Evans's (1996) suggested guideline on the classification of the correlation coefficient, an $r = 0.8973$ is considered ‘‘very strong’’. Therefore, this research will rely on the satellite rainfall data, which are complete and of high resolution. The data are merged with RALS data and each farmer is linked to an appropriate satellite rainfall observation point. The procedure used to assign a satellite point is as follows: assume there are two farmers, $F1$ and $F2$ in the grid for whom rainfall measurement is to be assigned. See figure 1.4 for illustration. Each farmer is bordered by two longitudes (E_1 and E_2 in figure 1.4) and two latitudes (N_1 and N_2 in figure 1.4). At the intersection of the longitudes and latitudes are four points, A, B, C and D, at which satellite rainfall readings are made.

Figure 1.4: Satellite rainfall points and farmers location



source: Author's construction

There are two ways to estimate satellite rainfall at farmer location. The first involves calculating the (weighted) mean of the four surrounding points. In this method, the weighting is based on the distances from a farmer to each point so that more weight is given to points that are closest. Although this is more appealing, there are practical issues with the computation of distances from all the four points. In the second method, a farmer is assigned rainfall readings from a point that is the nearest of the four.[9] For instance, F1 is nearer to point A than all the other points. Therefore, the farmer is assigned rainfall readings from point A. Similarly, F2 is closest to point C and is therefore assigned readings from C. Both methods are blind to topographical relief or terrain, which may affect the rainfall pattern. Although the second method has the weakness of ignoring readings from other points that may be roughly the same distance, such as for F2 in the illustration, the method is simple to implement. Rainfall variation between neighbouring points is also expected to be minimal given the short distances involved.

This thesis therefore employs the second method, where each farmer is assigned rainfall readings from the nearest point. The calculation of distance is accurate to a sub-millimetre, which rules out ties (Picard, 2012). This results in a greatest distance between the farmer and the satellite point of 19.3km with a mean of 10.4km.

The time span of the available data is too short to allow for a meaningful discussion of climate

9 In Stata, this is executed using the **geonear** command (Picard, 2012). This command computes the length of the shortest curve between the farmer and all rainfall points along the surface of a mathematical model of the earth, in order to identify the nearest point.

change and its impact on smallholder farmers. Therefore, this thesis confines itself to rainfall variability, which is detectable within the time span of the available data. However, the literature puts this subject in a much broader context, and extends the debate to climate change (Lal et al., 2001; McSweeney et al., 2012). Therefore, this thesis will still be drawn and make reference to climate change as it engages with literature.

Part II

ANALYTICAL CHAPTERS

CHAPTER 2

ASSESSING SMALLHOLDER FARMERS' ADOPTION OF CLIMATE ADAPTATION STRATEGIES

Chapter Abstract

This chapter evaluates drivers of climate adaptation among smallholder farmers in Zambia, using a mixed-methods approach. The chapter combines household survey data, satellite-rainfall data, and data from in-depth interviews with key informants to answer questions around climate adaptation. The chapter explores adaptation options that are available and model decisions to adopt in three prongs: a binary choice to adopt, the diversity of adoption, and the intensity of adoption.

The chapter finds that conservation farming is the main climate response strategy being promoted, alongside crop diversification, improved seed, irrigation, and diversification to other forms of agriculture, such as small livestock. However, the level of adoption of these practices remains low. There is evidence that farmers respond to rainfall shocks by adopting minimum tillage and crop rotation, which are part of conservation farming. Agricultural extension is also significant in promoting the adoption of minimum tillage and crop rotation while the adoption of organic soil cover is driven mostly by farming and livestock grazing cultures. The adoption of irrigation is driven by the availability of surface water, mostly along seasonal streams or reservoirs.

2.1 Introduction

Smallholder, dry-land farmers continue to dominate the agricultural sectors of many developing countries. According to the UN Food and Agriculture Organisation (FAO), about 80% of farmers in sub-Saharan Africa (SSA) and Asia, and 90% in Zambia are smallholders (IFAD, 2016), and remain highly dependent on rain-fed agriculture. A changing climate threatens the viability of the agricultural sector, especially in tropical zones of developing countries (Altieri and Koohafkan, 2008). With more erratic rains and more frequent occurrences of precipitation extremes, such as droughts, dry spells, and excessive rain, smallholder farmers are highly exposed to the effects of climate change. In addition, smallholder farmers lack the resources needed to cope with the effects of climate change, and therefore remain vulnerable (Smit and Pilifosova, 2001).

In order to help farmers to mitigate the effects of climate change, the Zambian government, with support from agricultural oriented cooperating partners and non-governmental organisations, has been promoting the adoption of climate-smart agricultural (CSA) practices, with an emphasis on adapting to increased variability in climatic variables and creating climate resilience (MoA and MFL, 2016). Practices being promoted include conservation farming (CF), which combines minimum tillage (MT), soil cover (SC), and diversified crop rotation (CR) practices (CFU, 2007, 2012). Other strategies being promoted are irrigation schemes, the cultivation of crops suited to the microclimate, and crop insurance (MoA, 2018a; MoA and MFL, 2016).

Despite these efforts, studies (Baudron et al., 2007; Ngoma et al., 2017; Zulu-Mbata et al., 2016) have shown low adoption of these practices among smallholder farmers. For instance, the adoption of minimum tillage remains at around 15%, while crop rotation and soil cover are below 50% and 60%, respectively (Arslan et al., 2014; Zulu-Mbata et al., 2016). Further, although Zambia has high irrigation potential in the dry season, the country is irrigating only about 6% of irrigable land (Akayombokwa et al., 2015; MoA, 2013c) and smallholder farmers irrigate only about 3% of the land they cultivate (Akayombokwa et al., 2015; Ngoma et al., 2017).

This chapter seeks to examine factors inhibiting the adoption of climate adaptation strategies and to explore ways to encourage their adoption. The chapter particularly examines the role of extension/farmer training services and of exposure to adverse weather in driving climate adaptation. In particular, the chapter attempts to address the following research questions.

- How are smallholder farmers responding to CC?
- What factors influence farmers' response to CC?
- What are the drivers of different adaptation strategies used by smallholder farmers?

2.1.1 Objectives

The overall objective is to determine the factors that drive the adoption of different CC adaptation strategies among smallholder farmers. The chapter is guided by the following specific objectives:

- to document the strategies that smallholder farmers are employing to mitigate the impact of CC.
- to investigate the determinants of the decision to adapt to CC.
- to investigate the determinants of the choice of different adaptation strategies by smallholder farmers.

2.1.2 Relevance of the chapter

Zambia, with support from agricultural oriented cooperating partners and non-governmental organisations, has invested resources to promote climate adaptation, including the adoption of conservation farming (CF) and irrigation. Evaluations conducted have, however, given mixed results. Some have shown moderate improvement in the number of farmers using CF and other strategies (Arslan et al., 2014; Zulu-Mbata et al., 2016). Other studies have shown some levels of dis-adoption or what Pedzisa et al. (2015a) called abandonment. This is where farmers revert to traditional methods (Habanyati et al., 2018).

Factors driving adoption, non-adoption, and dis-adoption of CC adaptation strategies have not been conclusively evaluated, but strong indications point to farmers' levels of education and awareness, the availability of supportive services such as specialised farming implements and chemicals, and the landholding system (Grabowski et al., 2014; Pedzisa et al., 2015a; Zulu-Mbata et al., 2016). Studies from other regions are of limited use in understanding decision-making that is affected by local and cultural contexts (Baudron et al., 2007; Lee, 2005). In addition, not many studies (Arslan et al., 2014) have done extensive evaluations on determinants of intensity of adoption using the proportion of land covered. Some have attempted to evaluate intensity using the number of practices adopted (Aryal et al., 2018; Pedzisa et al., 2015b). This chapter attempts to contribute to the literature by examining factors influencing not only the adoption of given agricultural practices as is common in the literature (Baudron et al., 2007; Grabowski et al., 2014; Pedzisa et al., 2015a; Zulu-Mbata et al., 2016), but also the tendency to adopt combinations of these practices and intensity with which farmers apply the practices. The findings of this chapter are important for helping to map the different strategies for climate adaptation and the challenges to them.

The chapter also brings in some methodological innovations. Firstly, the chapter proposes models that capture the role of exposure to objectively measured climate extremes in driving adaptation and employs methods that are robust to interrelationships among adaptation strategies. Not many studies on the topic (Arslan et al., 2018, 2015; Grabowski et al., 2014;

Ngoma et al., 2017; Teklewold et al., 2013a; Zulu-Mbata et al., 2016) have incorporated the effect of an objectively measured level of exposure to climate shock (Michler et al., 2019). This chapter also applies multivariate choice models, which account for complementarities among strategies (Arslan et al., 2014; Aryal et al., 2018; Kassie et al., 2013, 2015a; Mulwa et al., 2017; Teklewold et al., 2013a).

Secondly, the chapter benefits from a unique combination of quantitative data from the RALS, primary qualitative data from Agricultural Extension Officers (AEOs), and high resolution satellite rainfall data. This combination not only allows for the estimation of the state of adaptation but most importantly, provides context and intuition on the status of adaptation. Thirdly, the chapter proposes new measures of gender and level of education in the household which take into account all members of the household. This is in contrast to the tradition of considering the gender and education of only the head of household. There is evidence in the literature of the importance of other members in a household, whose demographics also matter in decision making (Acosta et al., 2019; Anderson et al., 2017; Zepeda and Castillo, 1997).

The rest of the chapter is organised as follows: Section 2.2 discusses background issues around climate change and adaptation in Zambia and section 2.3 reviews the literature. The methodology is discussed in section 2.4 and empirical analysis and discussion of the results in section 2.5. Section 2.6 presents the conclusions to be drawn from the earlier sections.

2.2 Background

The changing climate continues to threaten the viability of the agricultural sector, especially in tropical zones of developing countries (Altieri and Koohafkan, 2008). Climate change is said to have increased the occurrence of extremes in rainfall and temperature, which are key to crop yield for the vast number of smallholder farmers in developing countries. For instance, the Intergovernmental Panel on Climate change (IPCC), in its fifth assessment report (Hewitson et al., 2014; Olsson et al., 2014), warns that the risk from droughts and precipitation deficits is projected to increase and is likely to exacerbate the challenges facing rain-dependent smallholder farmers. In Zambia for instance, the UNDP (McSweeney et al., 2012) reported that the mean annual temperature has increased by $1.3°C$ while the mean annual rainfall has decreased by an average of $1.9mm$ per month per decade since the 1960s. The declining rains pose a danger to the viability of the agricultural sector, especially in the southern regions of the country where the reduction in rainfall has been more pronounced (AFAI, 2015).

In response, the Zambian government and its cooperating partners have been promoting a number of initiatives aimed at creating climate resilience especially among smallholder farmers. These include the promotion of climate-smart agricultural technologies, mainly conservation farming (CF) and irrigation. Other strategies include the promotion of crop varieties that are suitable for different regional microclimates, and crop insurance schemes (CFU, 2012; MoA and MFL, 2016).

The concept of conservation farming (CF) became more widely known in the 1990s in response to the declining rainfall (Baudron et al., 2007; Haggblade and Tembo, 2003). By the year 2000, the Ministry for Agriculture (MoA),[1] had adopted CF as an official government policy aimed at promoting climate resilience among farmers (MoA, 2001).

Since then, a number of institutions have been promoting CF and helping farmers to adopt it. For instance, the Conservation Farming Unit (CFU)[2] was formed to provide farmers with an enabling environment, knowledge, and practical experience to help them successfully adopt CF methods (CFU, 2012). The European Union (EU) also funded the Conservation Agriculture Scaling Up project (CASU),[3] with the aim to increase the number of farmers adopting CF through peer learning, improved inputs, and reliable markets (Kuntashula and Nhlane, 2018).

Irrigation is regarded as a promising solution to the problem of raising the agricultural productivity levels, especially in developing countries. For instance, Xie et al. (2014) report that productivity levels have increased in many areas where irrigation projects have been successfully implemented. Zambia boasts of vast water resources with irrigation potential estimated at 2.75 million hectares (MoA, 2013c). A number of initiatives and strategies are being undertaken to promote the adoption of irrigation schemes among smallholder farmers. For instance, the MoA has been implementing the Irrigation Development and Support Project (IDSP), 2011-2020, with support from the World Bank (WB).[4] The project's main objective is to promote the adoption of irrigation among smallholder farmers and to increase yields and marketed crop surplus through construction of large-scale irrigation infrastructure (WB, 2011).

Increased rainfall variability has also raised the need for crop insurance in the sector, in order to help farmers cope with climate-induced hazards. However, the uptake of crop insurance remains extremely low among smallholder farmers across the developing world. Plausible explanations for this include the poor understanding of the concept of insurance among farmers and the imbalance between the level of protection and farmers' willingness to pay (Fonta et al., 2018). The risk in rain-fed agriculture is high and the returns low, and therefore farmers can seldom afford the premium that underwriters would demand.

Despite all the above efforts, the adoption of these principles among smallholder farmers remains low in Zambia. For instance, Zulu-Mbata et al. (2016) have shown that the level of adoption

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[1] The Ministry for Agriculture has undergone a number of changes to its name. It has been called the Ministry of Agriculture and Cooperatives; the Ministry of Agriculture; the Ministry of Agriculture, Food and Fisheries; and the Ministry of Agriculture and Livestock in different periods. For easy reference, this chapter uses the Ministry of Agriculture nomenclature throughout.

[2] The CFU was set up in 1995 as a not-for-profit company to promote the adoption of CF among small- and medium-scale farmers. As of 2018, the unit operates in the *maize-belt* of Zambia covering the Eastern, Central, Southern and Western regions of the country.

[3] The CASU project (2013-2017) was implemented by FAO in partnership with the Ministry of Agriculture funded by the European Union through the 10th European Development Fund.

[4] Zambia signed a $US\$115m$ equivalent of the World Bank to fund development of irrigation projects across the country. The project includes construction of a dam, weirs and water extraction and conveyance infrastructure including canals and main pipelines and other supportive infrastructure such as roads and electrification.

of CF principles such as minimum tillage (MT) is around 15%, while crop rotation (CR) and soil cover (SC) are below 50% and 60%, respectively. Arslan et al. (2014) also found similar levels of adoption, putting the adoption of MT at below 10% and CR at around 50%. Similarly, the country is irrigating only about 6% of its irrigable land (Akayombokwa et al., 2015; MoA, 2013c; MoA and MFL, 2016). The area under irrigation is even smaller among smallholder farmers, who irrigate only about 3% of the land they cultivate (Akayombokwa et al., 2015; Ngoma et al., 2017), citing high cost of up-front investment, which these farmers can seldom afford (MoA, 2013c). Data on actual cost of irrigation is scarce but Xie et al. (2014) estimated it to lie between $US\$260$ and $US\$640$ annually per hectare in sub_Sahara Africa, depending on the kind of technology used and the source of water. The high cost has contributed to the confinement of irrigation along sources of surface water (MoA and MFL, 2016).

Crop insurance was virtually absent among smallholder farmers Zambia, until recently when the government introduced a mandatory weather-indexed insurance programme that operates alongside the Farmer Input Support Programme (FISP),[5] whose cover is limited to losses on FISP inputs only, and does not extend to crops grown from other inputs (MoA, 2018a,b). This chapter does not investigate the adoption of crop insurance for two reasons. First, crop insurance is a new product in the sector and uptake still low. Secondly, it is mandatory under FISP, with no farmer discretion in the decision to buy into it.

2.3 Literature Review

A number of studies have been conducted to understand factors affecting climate adaptation among smallholder farmers. Some have investigated the broader topic of adaptation (Komba and Muchapondwa, 2018; Nyanga et al., 2011) relying on multinomial and multivariate models, while others have looked at the adoption of specific strategies such as conservation farming (CF) (Arslan et al., 2014; Baudron et al., 2007; Chompolola and Kaonga, 2016; Habanyati et al., 2018; Zulu-Mbata et al., 2016) and irrigation (Ngoma et al., 2017). The results generally show low levels of adoption (Baudron et al., 2007; Ngoma et al., 2017), moderate increases in levels of adoption (Arslan et al., 2014; Zulu-Mbata et al., 2016), dis-adoption or abandonment in some cases (Habanyati et al., 2018; Pedzisa et al., 2015a), and partial adoption where the technology is not adopted in full or is applied only to a part of the cultivated land (Baudron et al., 2007). The drivers of adoption, non-adoption, and dis-adoption are inconclusive. This section reviews the literature on adaptation to increased rainfall variability among smallholder farmers, including the adoption of CF, highlighting gaps in the methodologies mentioned. The chapter highlights three broad areas of literature: econometric approaches in the literature in section 2.3.1, data issues in section 2.3.2, and key variables in the literature in section 2.3.3.

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5 FISP, as will be discussed later in chapter 3, provides subsidised inputs to eligible smallholder farmers. For instance, in the 2018/2019 farming season, farmers contributed $K300$ for a $K2000$ worth of inputs, with an additional $K100$ paid towards weather-indexed insurance (MoA, 2018a,b).

2.3.1 Econometric Approaches in the Literature

Econometric approaches to climate adaptation can be put into two broad categories. The first category (subsection 2.3.1.1), comprises models used to analyse dichotomous decisions on adopting a given strategy. The second category comprises models used to assess the depth of adoption. Again, the depth of adoption takes two forms: one based on the number of strategies adopted, referred to as multi-strategy adoption (subsection 2.3.1.2) and another based on the proportion of land to which each strategy is applied, also referred to as intensity of adoption (subsection 2.3.1.3).

2.3.1.1 Binary choice models

Studies evaluating farmers' choice to adopt CSA practices often rely on either binary or multinomial choice models. For instance, Arslan et al. (2014) and Zulu-Mbata et al. (2016) employed probit models in the analysis of the adoption of conservation farming (CF) in Zambia while Chompolola and Kaonga (2016), Habanyati et al. (2018), and Komba and Muchapondwa (2018) used logit models. In analysing the adoption of multiple strategies, studies such as Komba and Muchapondwa (2018), Nyanga et al. (2011), and Zulu-Mbata et al. (2016) relied on multinomial choice models. The *probit* and *logit* are standard estimation methods for binary response variables. The two models are developed from the same framework and the results are qualitatively similar (Papke and Wooldridge, 2008). The exposition here is based on Wooldridge (2010) and Greene (2012).

A farmer's choice to adopt a specific strategy is governed by a *latent* variable, I^*_{it}, which can be understood as the net benefit from adopting a given technology

$$I^*_{it} = X'_{it}\beta + \varepsilon_{it}, \quad t = 1, 2, \tag{2.1}$$

where X is a vector of plot characteristics such as hectarage, distance from homestead, and being in a dambo or not, and of household characteristics such as level of education, and ownership of draught cattle and land; β is a vector of corresponding parameters and ε_{it} is the error term. The farmer is assumed to adopt if I^*_{it} in eqn. 2.1 is positive and does not adopt if it is not.

$$\begin{aligned} Pr(Adopt|X) = p_{it} &= Pr(I^*_{it} > 0|X), \\ &= Pr(X'_{it}\beta + \varepsilon_{it} > 0|X), \\ &= Pr(\varepsilon_{it} > -X'_{it}\beta|X). \end{aligned} \tag{2.2}$$

The last line of eqn. 2.2 gives an inverse cumulative distribution function (cdf) of the error term, ε_{it}. In line with Wooldridge (2010, sec.15.3) and Papke and Wooldridge (2008), ε_{it} can be assumed to follow either a normal or a logistic distribution. The two distributions are similar, although the logistic distribution tends to be heavier in the tails, and the two distributions might differ in cases with a very low or very high proportion of “Yes” responses (Greene, 2012, p. 729).

Using the symmetrical properties of the two distributions, eqn. 2.2 transforms to

$$\begin{aligned} p_{it} &= P(\varepsilon_{it} < X_{it}^{'}\beta | X), \\ &= F(X_{it}^{'}\beta), \end{aligned} \tag{2.3}$$

where $F(\cdot)$ is the cdf of the error term, still assumed to follow a general distribution. The model in eqn. 2.3 will be a probit or logit model depending on the assumed distribution of the error term in eqn. 2.1. If the error is assumed to follow the standard normal distribution, then eqn. 2.3 becomes a probit model

$$p_{it} = \Phi(X_{it}^{'}\beta), \tag{2.4}$$

where $\Phi(\cdot)$ is the cdf of a standard normal distribution. If a particular β_j is positive, the probability of adopting CF increases as the corresponding x_j increases. When the error term in eqn. 2.1 is assumed to follow a logistic distribution, then eqn. 2.3 will transform to a logit model,

$$\begin{aligned} p_{it} &= \Lambda(X_{it}^{'}\beta) \\ &\equiv \frac{\exp(X_{it}^{'}\beta)}{1 + \exp(X_{it}^{'}\beta)} \end{aligned} \tag{2.5}$$

where $\Lambda(\cdot)$ is a logistic cdf. The logit model is often transformed to the *odds ratio* as shown in eqn. 2.6a and linearised to the log odds ratio in eqn. 2.6b

$$\left(\frac{P_{it}}{1 - P_{it}}\right) = \exp(X_{it}^{'}\beta), \tag{2.6a}$$

$$ln\left(\frac{P_{it}}{1 - P_{it}}\right) = X_{it}^{'}\beta. \tag{2.6b}$$

Again the same conclusion for β holds. If β_j is positive, the odds of adopting against not adopting increase with x_j.

Studies analysing binary dependent variables have used either the probit model in eqn. 2.4 (Abdulai, 2016; Arslan et al., 2014; Zulu-Mbata et al., 2016), or the logit model in eqn. 2.5 (Chompolola and Kaonga, 2016; Pedzisa et al., 2015b), or in some cases both. Papke and Wooldridge (2008) have argued that the choice is largely a matter of taste.

Multinomial models provide an alternative measure, looking at the choice of a strategy from a set of multiple alternatives. As in the binary choice cases, the multinomial probit and logit models are theoretically similar. However, the probit is less common, owing to its complicated response probability and difficult to obtain partial effects (see for instance Wooldridge (2010, p. 649) and Greene (2012, p. 801)).

A farmer is assumed to have J possible adaptation strategies in addition to no action, ($J = 0$). Each choice yields some level of utility. There will be $j+1$ possible levels of utility, corresponding to the choices, and the same number of error terms. Based on McFadden (1974), the farmer is assumed to choose a strategy that maximises utility. Assuming the errors follow the generalised *Type-I extreme value (Gumbel)* distribution (Greene, 2012, p. 803), the probabilities of the choices are given by

$$Pr(Y = j|X) = \frac{exp(X'_{ij}\beta_j)}{\sum_{j=0}^{m} exp(X'_{ij}\beta_j)}. \tag{2.7}$$

This model has $J + 1$ competing alternatives without a determinate position. It is made determinate by making one strategy (traditional/no-action method) the base, with the corresponding parameter $\beta_0 = 0$. The probabilities transform to

$$\begin{aligned} Pr(Y = 0|X) &= \tfrac{1}{1+\sum_{j=1}^{m} exp(X'_{ij}\beta_j)}, \quad \text{if} \quad j = 0, \quad \text{and} \\ Pr(Y = j|X) &= \tfrac{exp(X'_{ij}\beta_j)}{1+\sum_{j=1}^{m} exp(X'_{ij}\beta_j)}, \quad \text{for} \quad j = 1, 2, ..., J. \end{aligned} \tag{2.8}$$

The model in eqn. 2.8 provides the multinomial logit model for estimation and allows for the computation of odds ratios by pairwise comparison.

Binary choice models implicitly assume that farmers decide on the adoption of each strategy independently, while multinomial models assume that a farmer has to pick only one out of many strategies. The multinomial models are superior to the binary models because they allow for many alternatives. However, they have the general weakness of assuming independence of irrelevant alternatives (IIA) in the choice of strategies (Wooldridge, 2010, p. 501). Although adoption or adaptation has often been taken as a binary choice, there is an increasing realisation that it may be a stepped process (Andersson and D'Souza, 2014; CFU, 2012; Pedzisa et al., 2015b). Farmers adopt initial practices or strategies and incrementally adopt additional strategies.

Often, adaptation strategies tend to be complementary and can be bundled (Aryal et al., 2018; Kassie et al., 2013; Mulwa et al., 2017). There is evidence that adaptation strategies are complementary (Kassie et al., 2013, 2015a; Mulwa et al., 2017), implying increasing marginal benefits from additional adaptation practices adopted. The utility derived from one strategy is affected by the utilization of another strategy (Kassie et al., 2015a). This is reflected in the promotion of CF, which emphasizes the cumulative adoption of different principles (CFU, 2012). In the presence of such correlations, binary choice models are inefficient because they ignore the correlations in the error terms (Kassie et al., 2015a; Mulwa et al., 2017), while multinomial models are not appropriate.

Multivariate regression models have also been popularised in the analysis of multiple binary choice models, in line with Zellner's (1962, 1963) seemingly unrelated regressions (SUR) model. Multivariate models allow unrestricted interrelationship in the adoption of different strategies. For instance, Kassie et al. (2015a) in a four country study (Ethiopia, Kenya, Malawi and

Tanzania), Mulwa et al. (2017) in Malawi and Aryal et al. (2018) in Bihar state of India have shown that there is complementarity in the adoption of CSA strategies. The SUR probit approach is also supported by Teklewold et al. (2013a), who evaluated the adoption of multiple practices in rural Ethiopia and found strong complementarities and substitutabilities among practices.

A farmer's decisions to adopt one strategy is influenced by a portfolio of other strategies. Kassie et al. (2013) also used the multivariate probit on plot level data in four districts of Tanzania and provided empirical evidence that the adoption of different strategies is not independent, underscoring the need to provide farmers with information on strategy complementarity. The model provides for the evaluation of one strategy conditional on others, which is ideal in the evaluation of the adoption of related strategies. Under the multivariate model, a farmer makes a decision on each strategy, to adopt or not to adopt (Chib and Greenberg, 1998). Based on Greene (2012), the SUR probit, also referred to as multivariate probit (MVP) is developed from the following scenario.

There are $i = 1, 2, \ldots, n$ farmers and each has to make a dichotomous choice on $j = 1, 2, \ldots, J$ available strategies which might be interrelated. Therefore, there will be J latent variables Y_{ij}^* for each farmer, to inform the J observed choices. For the ith farmer,

$$\begin{array}{ccccc} y_{i1}^* & = & X_i'\beta_1 & + & u_{i1}, \\ \cdots & & \cdots & & \cdots, \\ y_{iJ}^* & = & X_i'\beta_J & + & u_{iJ}, \end{array} \tag{2.9}$$

where X_i is a vector of explanatory variables, β_j is a vector of corresponding parameters, and u_{ij} are disturbance terms which are assumed to follow a multivariate normal distribution with a zero conditional mean and the correlation matrix Σ. The observed variable y will take the values

$$y_{ij} = \begin{cases} 1 & \text{if} \quad y_{i1}^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad . \tag{2.10}$$

The multivariate models are superior to both the standard binary and multinomial models because they allow for some interaction among strategies (Mulwa et al., 2017). This is more appropriate to this paper, given that adaptation strategies may be complementary or substitutes and the adoption of one may be influenced by the adoption status of other strategies.

This chapter employs both the individual and SUR probits to model adoption. The combination is important to highlight the effect of correlation in the adoption of difference strategies.

2.3.1.2 Multi-strategy studies

The adoption of climate adaptation measures may not always be binary. More often than not, farmers have the option to adopt diverse strategies. This allows an evaluation on the basis of the number of strategies adopted. For instance, in the adoption of CF, it is argued that farmers adopt CF principles cumulatively and progressively from minimum tillage (MT) through conservation tillage (CT) and ultimately, CF (CFU, 2012).[6] In some literature (Pedzisa et al., 2015b; Sharma et al., 2010), this has been referred to as intensity of adoption while others have referred to it as diversity and reserved intensity to refer to the proportion of land on which the practice is applied (Andersson and D'Souza, 2014). Studies using the number of principles or practices employed as a measure of intensity have relied on the ordered probit or logit models (Pedzisa et al., 2015b; Teklewold et al., 2013a). This chapter will use the number of strategies adopted as a measure of diversity of adaptation, in line with Arslan et al. (2014).

To build an ordered probit or logit, Wooldridge (2010, sec.16.3) begins with eqn. 2.1 but assumes that there are J cut-offs. The intensity of adoption of, for example, CF is based on the latent variable I^*, defined earlier in eqn. 2.1. The observed number of strategies are now given by,

$$\begin{aligned} No \quad & Y = 0 \quad \text{if} \quad I^* \leq \alpha_0, \\ MT \quad & Y = 1 \quad \text{if} \quad \alpha_0 < I^* \leq \alpha_1, \\ CT \quad & Y = 2 \quad \text{if} \quad \alpha_1 < I^* \leq \alpha_2, \\ CF \quad & Y = 3 \quad \text{if} \quad I^* > \alpha_2. \end{aligned} \tag{2.11}$$

The probability of any ordered choice is derived from the probability of the latent variable falling in the respective intervals or bands. In general, the probability of $Y = j$, from eqn. 2.11 above, using the latent variable defined in eqn. 2.1 is given as,

$$\begin{aligned} P(Y = j|X) &= P(\alpha_{j-1} \leq I^* < \alpha_j), \quad \forall \, j = 0, 1, ...m, \\ &= P(\alpha_{j-1} \leq X_{it}^{'}\beta + \varepsilon_{it} < \alpha_j), \\ &= P(\alpha_{j-1} - X_{it}^{'}\beta \leq \varepsilon_{it} < \alpha_j - X_{it}^{'}\beta). \end{aligned} \tag{2.12}$$

The end limits, α_{-1} and α_m, are set to $-\infty$ and ∞ respectively. Using the $F(\cdot)$ for the cdf of the distribution of the error term ε_{it}, eqn. 2.12 is transformed to:

$$P(Y = j|X) = F(\alpha_j - X_{it}^{'}\beta) - F(\alpha_{j-1} - X_{it}^{'}\beta), \tag{2.13a}$$
$$= F(X_{it}^{'}\beta - \alpha_{j-1}) - F(X_{it}^{'}\beta - \alpha_j). \tag{2.13b}$$

The transformation from eqn. 2.13a to 2.13b relies on the symmetry of the appropriate distribution of the error term. If the error term follows a standard normal distribution, then eqn. 2.13 will be an *ordered probit*. If a logistic distribution, then an *ordered logit*. In these models, the probability is like a wave moving from lower to higher bands as X increases (assuming β is positive). The major weakness of the ordered probit model is that it is concerned only with the number of components adopted and is blind to the actual composition of each package of adaptation strategies.

[6] Farmers progressively adopt CF, moving from minimum tillage (MT), to conservation tillage (CT) by retention of crop residues and finally to CF when they include crop rotation.

2.3.1.3 Intensity of adoption

The term intensity of adoption has been used differently in the literature (Andersson and D'Souza, 2014). One branch of literature measures intensity by the number of practices adopted, which this chapter refers to as diversity of adoption. Another branch uses the proportion of land under a particular practice as the measure of intensity of adoption (Arslan et al., 2014; Ngoma et al., 2017; Pretty and Bharucha, 2014). This is the definition used in this chapter.

Studies looking at the intensity of adoption, as defined in this chapter, use the proportion of land under each practice as a measure of intensity (Arslan et al., 2014; Grabowski et al., 2014; Kassie et al., 2013). The use of 'proportion' of land under each adaptation strategy introduces possible *censoring* at zero and one. The two bounds deposit a disproportionately large number of observations in the corners of the distribution, rendering standard regression techniques inappropriate. The predicted values from an OLS regression, for such a variable, can never be guaranteed to lie in the *zero-to-one* interval (Papke and Wooldridge, 1996).

This presents two options on the appropriate model: a fractional response model and the censored regression model (Arslan et al., 2014; Loudermilk, 2007; McDonald, 2009; Ramalho et al., 2010). The choice between the fractional response models and tobit models is mainly a discussion of whether the data is generated from a censored data generating process. The fractional response model is appropriate for fractional dependent variables such as proportions. For instance, Papke and Wooldridge (2008) chose the fractional response model over the tobit because, although their response variable was seemingly bounded from below by zero, there were no observations at zero. Similarly, McDonald (2009) has advocated against the application of the tobit model in data envelopment analysis (DEA) efficiency analyses on the basis that "efficiency scores are not generated by a censoring process".

However, the fractional response model may not be appropriate when the dependent variable is evidently censored and therefore has high masses of observations in the corners (Loudermilk, 2007). A censored regression model or tobit model is arguably more appropriate for such scenarios. For instance, Hoff (2007) has shown that it is common to apply the two-limit tobit model on DEA efficiency scores, which are bounded in the interval (0,1], on the basis that "DEA scores resemble corner solution variables". Similarly, Arslan et al. (2014) used a random effects tobit to model the share of land allocated to an adopted farming practice while Grabowski et al. (2014) and Kankwamba et al. (2018) used the tobit model on the proportion of land and degree of crop diversification, measured using the Simpson index of diversification, respectively, which are not only censored but are also fractional. The argument put forward by McDonald (2009) on the choice between the tobit and fractional model is not on whether the tobit is appropriate for fractional variables or not. Rather, the argument is on whether or not the data is actually censored.

The tobit model is also based on the index function in eqn. 2.1, replicated here in eqn. 2.14a, where the error term ε is assumed to be normally distributed. The observed level of intensity I will be given by eqn. 2.14b.

$$I_{it}^{*} = X_{it}^{'}\beta + \varepsilon_{it}, \quad t = 1, 2, \tag{2.14a}$$

$$I_i = \begin{cases} 0 & \text{if} \quad I_{it}^{*} \leq 0 \\ I_{it}^{*} & \text{if} \quad 0 < I_{it}^{*} < 1 \\ 1 & \text{if} \quad I_{it}^{*} \geq 1 \end{cases} . \tag{2.14b}$$

The model of this nature combines both the binary choice model for the censored portions and the linear regressions for the uncensored parts (Greene, 2012, p. 764) and represents a two stage decision process. The farmer chooses to adopt in the first decision and then decides on the depth of adoption as a second decision. The conditional expectation of the intensity or depth of adoption, conditional on adoption intensity being within $A = (b_l, b_u)$, based on McMillen and McDonald (1990), is given by

$$E(y|b_l < I_{it} < b_u) = X_{it}^{'}\beta + \sigma \frac{\phi\left((b_l - X_{it}^{'}\beta)/\sigma\right) - \phi\left((b_u - X_{it}^{'}\beta)/\sigma\right)}{\Phi\left((b_u - X_{it}^{'}\beta)/\sigma\right) - \Phi\left((b_l - X_{it}^{'}\beta)/\sigma\right)}, \tag{2.15}$$

where the latter part of the expression is the extension of the inverse Mills ratio (Greene, 2012, p. 764). The inverse Mills ratio is necessary to adjust for the non-zero probabilities in the corners McMillen and McDonald (1990). The $\Phi(\cdot)$ and $\phi(\cdot)$ are normal cdf and pdf respectively, while b_l and b_u are lower and upper bounds respectively. For a ratio dependent variable, as used here, the bounds are set to zero and one respectively. The major advantage of tobit models is their ability to measure the intensity of adoption of strategies individually and to correct for the disproportionally high number of corner observations. This chapter will build on this model.

2.3.2 Data in the Literature

There are two broad categories of data in the literature. The first group relied on district case studies. Examples include Chompolola and Kaonga (2016) and Habanyati et al. (2018), on one district each in Zambia, and Kassie et al. (2013) and Komba and Muchapondwa (2018) on selected districts of Tanzania. Studies of this nature are highly informative on their particular study districts but less informative beyond those districts. Farmers' behaviour is influenced by local factors, such as microclimate, and farming culture or system (Baudron et al., 2007; Lee, 2005; Zulu-Mbata et al., 2016), which will vary from district to district. Therefore, findings from one set of districts may not always be applicable to other contexts.

The other category has used nationally representative surveys of farmers. For instance, Arslan et al. (2014, 2015) used the two rounds of the Rural Incomes and Livelihoods Surveys (RILS) conducted in 2004 and 2008, a nationally representative survey of small-scale farmers in Zambia, while Ngombe et al. (2014) used 2008 round of RILS only. Others such as Ngoma et al. (2017) and Zulu-Mbata et al. (2016) used the same data as this chapter. Similar surveys were used by Mulwa et al. (2017) in Malawi, Michler et al. (2019) in Zimbabwe, and Kassie et al. (2015a) in a four-country study involving Ethiopia, Kenya, Malawi, and Tanzania. Grabowski et al. (2014) used two waves (2002 and 2011) of a census of cotton input distributors to study the adoption of MT among smallholder cotton farmers in Zambia. Country-level datasets are informative on all the micro-level local contexts of adaptation. For instance, they allow for the control of geographical variations within a country. However, the use of quantitative data in isolation fails to provide context to the findings. Generally, while such data allow for the examination of levels and drivers, they do not answer the 'Why?' question.

Other studies, such as Ngoma et al. (2017) and Zulu-Mbata et al. (2016), supplemented quantitative data with qualitative data. Such combinations have the advantage of providing contexts to quantitative findings and are useful for understanding the causal chain. For instance, Ngoma et al. (2017) used the qualitative component to assess the governance, marketing and institutional arrangements available to support the adoption of irrigation in Zambia.

2.3.3 Key Variables in the Literature

The types of variables and how they are measured have the potential to affect research findings. This section examines how the literature has treated key variables in the study of climate adaptation.

2.3.3.1 Measurement of rainfall

The effectiveness of new farming technologies, and hence their attractiveness to farmers in the rain-fed agricultural sector, is influenced by the adequacy and distribution of rainfall (Andersson and D'Souza, 2014; Grabowski et al., 2014; Kassie et al., 2013). However, a number of studies that sought to look at the adoption of climate-related agricultural practices failed to incorporate measures of rainfall. Others failed to obtain objectively measured local rainfall. For instance, Kassie et al. (2013) used individual farmers' perceptions of the timeliness, adequacy and distribution of rainfall as a measure of rainfall shock in Tanzania. Similarly, Komba and Muchapondwa (2018) used farmers' own observations of rainfall and temperature. The major drawback of such approaches is that perceptions are likely to be influenced by the level of sensitivity, resilience or preparedness of each farmer.

Arslan et al. (2014, 2015) obtained objectively measured rainfall data. However, due to lack of geo-references in the main data, rainfall data are aggregated at district level. This has the potential to mask within-district variations in rainfall that have an impact on farmer behaviour. Michler et al. (2019) aggregated similar high-resolution satellite rainfall data at the ward level in Zimbabwe. They compute a measure of rainfall shock, based on (Ward and Shively, 2015), as a normalised seasonal deviation of rains from the long-term average:

$$R_{it} = \frac{r_{it} - \bar{r}_i}{\sigma_{r_i}}, \tag{2.16}$$

where r_{it} is the amount of rainfall in a season and $\bar{r}_i$ is the long-term rainfall average. There are two shortcomings to Michler et al.'s (2019) approach. First, aggregating rainfall data at ward level may not give good estimates of rainfall at household level. Secondly, the formula does not capture within-season maldistribution of rainfall, which might equally be important in shaping farmers' response (Lalani et al., 2017).

2.3.3.2 Human capital

Household demographic characteristics have the potential to affect decisions on which farming assets to purchase and which farming practices to adopt (Chompolola and Kaonga, 2016; Mulwa et al., 2017). For instance, households with higher levels of education are more likely to access and comprehend information on new technologies. Many studies use the level of education and gender of the household head, implicitly assuming that the head is the sole decision-maker (Carney and Carney, 2018; Kassie et al., 2013; Meijer et al., 2015; Pender and Gebremedhin, 2008). However, studies looking at household decision making have shown the importance of other members of the household, such as the spouse, in decision making (Acosta et al., 2019; Anderson et al., 2017; Zepeda and Castillo, 1997).

In addition, the absence of functional factor markets in rural settings limits labour inputs to household labour (Gollin, 2014; Pedzisa et al., 2015b). Therefore, household size, age, and gender composition are important indicators of labour availability in a farming household. In order to exclude minors, studies use the number of adults a household (Arslan et al., 2014; Pedzisa et al., 2015b; Xu et al., 2009).

2.3.3.3 Physical capital

Ownership of farming equipment has the potential to aid adoption of better, climate-suited, farming practices. Studies traditionally include measures of ownership of physical capital such as draught animals (Chompolola and Kaonga, 2016; Kassie et al., 2013; Mulwa et al., 2017), farming implements (Kassie et al., 2015a; Teklewold et al., 2013a) and land (Arslan et al., 2014; Feliciano, 2019; Maggio et al., 2018; Zulu-Mbata et al., 2016). Some studies look at land from a tenure or security perspective, arguing that farmers with security of land tenure have higher chances of adopting sustainable farming practices such as CF (Feliciano, 2019; Kassam et al., 2019; Kassie et al., 2015a). These define tenure using a dummy variable, often separating more secure landholding systems from less secure systems.

2.3.3.4 Crop diversification

Crop diversification has been promoted for its effects on spreading the risk of crop failure, ensuring security for food, nutrition, income, and sustainable management of natural resources (Basavaraj et al., 2016; Bhattacharyya, 2008; Lal et al., 2001; MTENR, 2010). Household-level diversity of cultivated crops provides a basis for the adoption of new farming practices such as CF (Kassie et al., 2013; Liebman and Dyck, 1993). With a diversified crop base, farmers have the liberty to practice crop rotation (Kassie et al., 2013; Liebman and Dyck, 1993). Studies often measure the level of crop diversity using the Simpson index of diversification (SID) (Jones et al., 2014; Kankwamba et al., 2018) based on Simpson (1949). However, no study has attempted to include the level of crop diversity as an explanatory factor in the adoption of other CSA practices.

A few limitations are worth noting from the existing literature on climate adaptation and its extent of application on Zambia. First, most studies were based on case studies, which are inappropriate for understanding decisions that are influenced by culture, microclimate, or farming systems (Baudron et al., 2007; Zulu-Mbata et al., 2016). Secondly, despite acknowledging that adoption is driven by exposure to extreme weather events, most studies failed to incorporate the role of climatic variables in the models. Thirdly, many studies used strategy-specific adoption models which ignore complementarities among different strategies. This chapter attempts to use a country-representative dataset, incorporate objectively measured rainfall shocks, and employ multivariate models that are robust to interdependence in adoption among strategies.

This chapter benefits from a rich combination of datasets, which allows the computation of all the important variables discussed above. In addition, the chapter proposes some modifications to variables. For instance, it proposes a better measure of rainfall shock, deviates from the tradition of considering the gender and education of the head only, and measures household size by the number of labour-providing members.

2.4 Methodology

This chapter employs a mixed-methods approach, incorporating both quantitative and qualitative approaches. The quantitative approach utilised the Rural Agricultural Livelihood Surveys (RALS) and high-resolution satellite rainfall data to evaluate or examine factors that promote or hinder the adoption of different climate-adaptation farming technologies. A qualitative approach was used to understand and map out the climate adaptation support framework available to help farmers adapt and understand some of the factors driving adaptation. In-depth interviews were conducted with district-level key informants in the agricultural sector. As noted by Trotter (2012), mixed-methods approaches incorporate the strengths of both approaches while simultaneously reducing on the limitations of each.

2.4.1 Model Specifications

In order to understand the extent of adoption or use of different climate adaptation measures, a quantitative approach using various econometric models is used. The econometric approach tackles adaptation in three prongs: (1) adaptation strategy choice by farmers, (2) diversity of adaptation, measured by the number of practices or strategies adopted, and (3) intensity of adoption, measured by the proportion of land under a given adaptation strategy.

In order to account for clustered sample selection in line with Abadie et al. (2017), the standard errors are clustered at the standard enumeration area (SEA) level. Abadie et al. (2017) have argued for clustered standard errors whenever the sampling is clustered as is the case with the RALS data.

2.4.1.1 Choice to adopt

This chapter uses a multivariate probit model based on Zellner's (1962, 1963) SUR model to analyse the adoption of different climate adaptation strategies. The SUR model is appropriate because it estimates the adoption of different strategies simultaneously, allowing the random errors to be related across adaptation strategies.

A latent variable is defined, based on eqn. 2.9. When deciding to adopt each strategy, a farmer is assumed to perform a cost-benefit analysis, based on available resources, including information. The expected net benefit y^*_{ijt} from adopting strategy j at time t is unobserved, but assumed to be a linear combination of household and plot characteristics, training received, rainfall, and unobserved characteristics. Household characteristics such as size, level of education, gender, and age composition all affect the appropriateness and effectiveness with which the household will implement a given strategy and hence the net benefit. The latent variable for the ith farmer deciding to adopt strategy j at time t is given by

$$y^*_{ijt} = X^{'}_{ijt}\beta_j + \delta_j R_{it} + \gamma_j E_{ij} + u_{ijt}, \tag{2.17}$$

where X is a vector of household and plot characteristics, β is a vector of corresponding parameters and u_{ijt} is the error term. The E_i is a binary measure of having received extension or training services on a particular practice and R_{it} is a measure of rainfall shock as defined later in eqn. 2.26.

The actual level of the latent variable is not observable. Instead, only the dichotomous decision on each strategy or practice is observed as:

$$y_{ijt} = \begin{cases} 1 & \text{if} \quad y^*_{ijt} > 0 \\ 0 & \text{if} \quad y^*_{ijt} \leq 0 \end{cases} . \tag{2.18}$$

The model in eqn. 2.17 can be expressed in a more compact form as follows:

$$Y_i^* = Z_{ij}B + \varepsilon_i, \tag{2.19}$$

where Y is a vector of dichotomous plot level response variables, and Z is a $J \times K$ matrix containing X, R and E from eqn. 2.17 and expressed in the form,

$$Z_i = \begin{bmatrix} x_{i1} & 0 & \dots & 0 \\ 0 & x_{i2} & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & x_{iJ} \end{bmatrix}, \quad i = 1, 2, \dots, n, \tag{2.20}$$

and B is the corresponding vector of parameters. The term ε is a vector of disturbance terms assumed to follow a joint normal distribution with conditional mean zero and covariance matrix Σ, which is standardised to a matrix of correlation coefficients, $\varepsilon_i \sim N(0, \Sigma)$ (*see* Chib and Greenberg (1998)).

2.4.1.2 Diversity of adaptation

This chapter employs an ordered probit model to evaluate the number of strategies adopted. The ordered probit model, though similar to the standard probit, allows for more ordered values of the dependent variable. The framework for the ordered probit is given in eqn. 2.13. The ordered probit, with appropriate variables added, will be given by

$$P(Y = j|Z) = \Phi\left(Z_{it}\theta - \alpha_{j-1}\right) - \Phi\left(Z_{it}\theta - \alpha_j\right), \tag{2.21}$$

where again $\Phi(\cdot)$ is the cdf of a standard normal distribution, Z is a vector defined in 2.19 containing household characteristics X, the rainfall shock R and training E, and α_{j-1} and α_j are lower and upper bounds respectively. The corresponding marginal effects are computed as

$$\frac{\partial P(Y = j|Z)}{\partial x_k} = [\phi(Z_{it}\theta - \alpha_{j-1}) - \phi(Z_{it}\theta - \alpha_j)] \cdot \beta_k, \tag{2.22}$$

where $\phi(\cdot) = \Phi^{'}(\cdot)$ is the density function. The marginal effects of middle bands will depend on the comparative proximity of the latent variable to the two cut-off points α_{j-1} and α_j. If $Z_{it}\theta$ is closest to the lower cut-off point α_{j-1}, the marginal effect will be positive for a positive β_k. Similarly, when $Z_{it}\theta$ is closest to the upper cut-off point α_j, the marginal effect is negative.

2.4.1.3 Intensity of adoption

In addition to analysing the decision to adopt, it is also important to look at the intensity of adoption. The intensity of adoption is important to understand the level, depth or degree of adoption of farming practices. Intensity is defined, in line with Arslan et al. (2014), as the proportion of land cultivated under the adopted strategies. As a ratio, the variable is bounded in $[0, 1]$, with legitimate border cases (Arslan et al., 2014; Loudermilk, 2007). There are farmers who have yet to adopt certain strategies and those that commit all their fields to given strategies. As table 2.9 shows later, there is a high proportion of cases at zero and one. Fractional regression models are traditionally used on fractional dependent variables (Papke and Wooldridge, 1996; Ramalho et al., 2010). However, as demonstrated in section 2.3.1.3 and in view of the high proportion of corner cases as shown in table 2.9, this would be more appropriately dealt with using a censored regression or the tobit model.

Because of the potential correlations in the adoption of practices, a SUR based tobit regression may be used. The SUR model, based on Zellner (1962, 1963), is able to adjust for the potential correlations in the disturbance terms. However, in view of weak evidence for the presence of correlations in the adoption of practices in table 2.6 and the complexity of computing SUR based tobit, there is little motivation for the SUR tobit over standard tobit. Therefore, the chapter estimates a tobit regression model based on Greene (2012, Sec.19.3.2) and the latent variable defined in eqn. 2.17. The model is of the form.

$$y_{it} = X_{it}^{'}\beta + \delta R_{it} + \gamma E_i + \varepsilon_{it}, \tag{2.23}$$

where y_{it} is the proportion of land cultivated under a particular strategy and other variables are as defined in the model in eqn. 2.17. As in the probit models, the error term is assumed to be normally distributed.

Since the model is censored on both ends, the observed values of the index I will be

$$I_{ij} = \begin{cases} 1 & \text{if} \quad y_{ij}^* \geq 1, \\ y_{ij}^* & \text{if} \quad 0 < y_{ij}^* < 1, \\ 0 & \text{if} \quad y_{ij}^* \leq 0. \end{cases} \tag{2.24}$$

When the lower and upper bounds are set to zero and one respectively, the tobit model in eqn. 2.15 simplifies to

$$E(y|0 < I_{it} < 1) = X_{it}^{'}\beta + \sigma \frac{\phi\left((-X_{it}^{'}\beta)/\sigma\right) - \phi\left((1 - X_{it}^{'}\beta)/\sigma\right)}{\Phi\left((1 - X_{it}^{'}\beta)/\sigma\right) - \Phi\left((-X_{it}^{'}\beta)/\sigma\right)}, \tag{2.25}$$

where $\Phi(\cdot)$ and $\phi(\cdot)$ are the cdf and pdf of a normal distribution, respectively. The tobit regression corrects the results for the high number of observations that may be deposited in the two ends. This model has been used by in a number of studies involving censored fractional dependent variables (Arslan et al., 2014; Kankwamba et al., 2018; Loudermilk, 2007).

2.4.2 Data

The main data for this chapter are the Rural Agricultural Livelihood Surveys (RALS) described in section 1.3.1. The data have household and plot level data on land and crop management which reveal the adoption of different climate-adaptation strategies including CF (minimum tillage, permanent soil cover, and crop rotation) and irrigation, as well as data on demographics, farmland characteristics and use, input access, and other economic variables such as ownership of draught animals and other farming implements. In addition, the data have geographical inputs which allow *geolocation* and linkage with geo-coded rainfall data.

The chapter also include the high resolution satellite rainfall data from CHIRPS as described in section 1.3.3. Each household is linked to the nearest satellite rainfall measurement in order to provide an objective measure of rainfall at the household level. In addition, qualitative data from the key informant interviews with agricultural extension workers in Chisamba and Monze districts, described in subsection 1.3.2, are added. The qualitative approach solicited detailed information on the available supportive framework for climate adaptation, as well as the challenges and opportunities that each adaptation strategy presents. In the citation of key informants, MO denotes Monze and CH denotes Chisamba, while M and F denote male and female respondents, respectively.

2.4.3 Operational Definitions of Variables

Adaptation to rainfall variability or adoption of CF continues to receive increasing attention among researchers. However, there does not seem to be convergence on how these terms are defined (Andersson and D'Souza, 2014). This sub-section provides operational definitions of the key variables used.

2.4.3.1 Dependent variables

Minimum tillage generally refers to reduced tillage practices being implemented, especially as part of the broader CF (Andersson and D'Souza, 2014). Farmers will practice MT in different ways, from the use of direct seeding and planting basins to mechanical ripping. The RALS has data on the use of the following nine tillage methods that are practised in Zambia: (1) conventional hand hoeing, (2) planting basins, (3) zero tillage, (4) ploughing, (5) ripping, (6) ridging, (7) bunding, (8) mounding, and (9) broadcast the seed. This chapter considers practices (2), (3), (5), and (9) as comprising MT and the rest as conventional tillage.

Crop rotation refers to the practice of rotating crops planted on each area of land or temporal diversification (Liebman and Dyck, 1993), with an emphasis on a mix of legumes and non-legumes. The RALS solicited information on what crop was planted in each field in the season of data collection and the two seasons before. If at least two different crops were planted in the three seasons, the farmer is considered to have practised crop rotation on that field, without placing emphasis on the inclusion of legumes as defined by FAO (2019).

Soil cover refers to the practice of maintaining an organic soil cover in fields. In the RALS, respondents were asked what they did with the crop residue from the previous farming season. There were eight possible responses: (1) left in field then ploughed/incorporated into field, (2) left in field and grazed by animals, (3) burned in field, (4) cut and spread on the field, (5) cut, removed from field and fed to animals, (6) cut and removed from field for other household use, (7) new field, cleared later, and (8) left in field or did nothing. This chapter takes practices 1 and 4 as constituting the practice of soil cover or residue retention. A farmer that implemented either of the two is considered to have provided soil cover on that field.

On irrigation, the RALS listed all the fields that a responding farmer owned or cultivated. For each field, respondents were asked to indicate if they irrigated that field. Therefore, the adoption of irrigation is defined as self-reported by respondents in respect of each field. A farmer is considered to have adopted irrigation if he/she reported irrigating at least one field.

2.4.3.2 Rainfall shock

Rainfall shock measures the degree of extreme variation in rainfall for each location and season, and indicates the level of exposure to rainfall variability. It is conceptualised as a measure of how the seasonal rainfall deviates, either too low or too high, from long-term averages.

This chapter improves on measure used by Michler et al. (2019) in eqn. 2.16 to provide an alternative measure based on standardised monthly deviations from the long-term monthly averages, as shown in eqn. 2.26a. The shock defined in equation 2.26a captures *within-season* variations in rainfall such as droughts, short dry-spells, or excessive rains. The formulas measure a standardised deviation of each month's rainfall from the long-term average for that month $\bar{r}_{im}$ which is then summed over twelve months.[7]

$$R_{it} = \sum_{m=1}^{12} \frac{(r_{itm} - \bar{r}_{im})^2}{\sigma_r^2}, \tag{2.26a}$$

$$R_{it}^{-} = \sum_{m=1}^{12} \frac{(r_{itm} - \bar{r}_{im})^2}{\sigma_r^2}, \text{ if } r_{itm} < \bar{r}_{im}. \tag{2.26b}$$

In eqn. 2.26b, the shock is restricted to measuring rainfall deficits only. This is important in order to isolate the impact of dry spells and droughts from general rainfall extremes.

2.4.3.3 Training/extension services

Farmer training plays a critical role in building capacity among farmers to take on new technologies (Carter et al., 2014; Komba and Muchapondwa, 2018). Training may be offered on a broader agricultural topic or be specific to given climate-smart agricultural (CSA) practices.

[7] In Zambia, an agricultural season runs from October through September (Mason et al., 2013), and this chapter counts the months accordingly.

In this chapter, training is treated as a binary indicator of receipt of advice or information on a given aspect of agriculture.

2.4.3.4 Human capital

Age is the age is years of the head of household. Age indicates one's accumulation of experience and knowledge of production systems and hence the capacity to appreciate new technologies (Kassie et al., 2013). Beyond a certain age, the elderly become less experimental, favouring conventional or traditional farming methods. Age is expected to have a decreasingly positive effect on adaptation.

This chapter measures education using the highest level of education in the household, irrespective of whether it is attained by the household head or another member of the household, as suggested by Anderson et al. (2017) and Zepeda and Castillo (1997). Data show that household heads are the most educated in about 44% of households, after excluding members below 18 years of age. Gender is the proportion of males amongst members who are older than 15 years. Consequently, a male-dominated household is defined as a household with a greater proportion of males relative to females. Male-dominated households are expected to have a higher probability of adopting new technologies.

2.4.3.5 Household size

Due to a shortage of labour markets, smallholder farmers mostly rely on family labour (Gollin, 2014; Pedzisa et al., 2015b). Therefore, household size is a proxy for labour availability in a farming household. The challenge is in defining a boundary between minors and adults who can contribute to labour. There is no objective guidance on this, only examples: Arslan et al. (2014) used 15 years while Xu et al. (2009) used 14 years. Noting the contribution of child labour in rural settings (Jain, 2007), this chapter uses 15 years, in line with Arslan et al. (2014). Household size is therefore measured as the number of members who are above the age of 15.

2.4.3.6 Social networks

Social networks are important for sharing information and resources in rural households (Kassie et al., 2013). Social networks also facilitate access to community resources and are an important avenue for accessing government support such as subsidies. In this chapter, it is measured as a binary variable indicating membership in a farmer cooperative, group or association by any member of the household. This is expected to have a positive impact on the uptake of adaptation measures.

2.4.3.7 Market access

Proximity to markets or motorways provides ease access not only to markets for inputs and output, but also to access to new information. Remoteness is measured by the distance to a tarred road and farmers closer to markets or motorways are expected to have a higher chance of adopting new technologies, compared to very remote farmers.

2.4.3.8 Physical Capital

Farmer categories are A if cultivating less than $2ha$, B if cultivating $2-5ha$, and C if cultivating more than $5ha$. Ownership of enabling or specialised farming assets changes the cost of adopting new farming technologies. For instance, a ripper is designed for MT and owning one is hypothesised to increase the likelihood of a farmer adopting MT, while ownership of draught cattle is expected to ease adoption of practices that require more farm power, such as early planting (Dibbits, 1999). However, the impact on the adoption of MT is indeterminate. With more draught power, intensive tillage becomes more attractive. At the same time, more draught power may encourage the use of MT combined with secondary tillage for weed control.

Ownership of physical capital is measured by binary indicators of ownership for each farming asset, including mouldboard plough, ripper, knapsack sprayer, or other assets as of the 1st of May preceding the farming season under observation.[8]. Measuring ownership of farming assets prior to the season helps to avoid a potential endogeneity problem, in which asset ownership is influenced by decisions on which farming technologies to adopt. In addition, cattle ownership is measured by the number of cattle owned.

2.4.3.9 Land Size

Zulu-Mbata et al. (2016) found a non-linear relationship between land size and adoption of CF on account of land inadequacy. This chapter argues that the adequacy of land is not in its absolute size, but in its relative size. Therefore, this chapter calculates land adequacy (LA) as a ratio of owned land to cultivated land: $LA = \frac{L_O}{L_C}$, where L_O is the area of land owned and L_C is the area of land cultivated. LA will be greater than one if a household has more land than it uses and *vice versa*. Farmers may cultivate more land than they own by renting or borrowing fields.

2.4.3.10 Crop Diversification

This chapter measures crop diversification at a household level using the Simpson index of diversification (SID), based on the *Herfindahl-Hirschman Index* (HHI).[9] The index can be computed at either the hectarage or output levels. At the hectarage level, the index reveals farmers' actions or efforts towards diversification. When computed at the output level, it shows the level of diversification in output, which might differ from the result for hectarage if crop failure is not independent of crop type. In this thesis, the index is computed at the hectarage level, as employed by Kankwamba et al. (2018).

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[8] In Zambia, farming seasons run from October through September. See note 7 on page 39

[9] The Herfindahl-Hirschman Index is commonly used in business and finance as a measure of market concentration.

The RALS data have information on crops grown and areas covered by each crop. Using that information, the SID is calculated as follows:

$$HHI = \sum_{i=1}^{n} P_i^2, \quad \text{where } P_i = \frac{A_i}{\sum_{i=1}^{n} A_i} \tag{2.27a}$$

$$SID = 1 - HHI \tag{2.27b}$$

where A_i is the total area under each crop. The index will range between zero for a monocropping farmer and close to one for a perfectly diversified farmer.

2.4.3.11 Plot/Field characteristics

Plot or field characteristics can also play an important role in influencing the decision to implement climate-adaptation strategies. For instance, the distance of the field from the homestead, its perceived fertility, and whether it is prone to flooding have all been found to impact the decision to adopt various farming practices (Kassie et al., 2013; Teklewold et al., 2013a; Zulu-Mbata et al., 2016). This chapter measures distance from the homestead in kilometres. Dambo is a binary measure of whether the field is located in a wetland/dambo area; ‘‘floods’’ takes a value of one if the field is prone to flooding and zero otherwise. Zambia has a dual land-tenure system: the leasehold system, mainly on state land, and the customary systems. According to the Ministry of Lands and Natural Resources (MLNR, 2017), the leasehold system provides documented, state-guaranteed, rights of ownership and security of tenure, while the customary system lacks formal land documentation and the security of tenure is based on traditional institutions. The leasehold system has recognised advantages, including better security of tenure and the ability to use it for collateral (Tagliarino, 2014). This chapter defines tenure of land as one if under leasehold tenure and zero otherwise.

2.5 Empirical Analysis

This section analyses the data. Subsection 2.5.1 provides descriptive analysis and subsection 2.5.2 presents the main findings and discussion.

2.5.1 Descriptive Analysis

Descriptive statistics help to describe the basic features of the data and provide some context necessary for understanding the results. This section provides a descriptive analysis of the demographic information (subsection 2.5.1.1), ownership of farming assets (subsection 2.5.1.2), adoption of various farming practices (subsection 2.5.1.3), and rainfall performance in the period under review (subsection 2.5.1.4).

2.5.1.1 Demographic information

Selected demographic information about the respondent farmers is presented in table 2.1.

Table 2.1: Demographic information of RALS farmers

Variable	Obs	mean	sd	min	max
gender (% of males)	7,931	49.2	19.2	0	100
age	7,931	48.66	14.8	16	105
education	7,931	8.15	3.2	0	18
No. of adults	7,931	4.25	2.22	1	21
distance to tarred road	7,930	27.57	35.98	0	300

The majority of household heads are males (79%), with an average age of 49 years. The highest level of education in a household is 8 years, corresponding to the first year of secondary education.[10] The average distance of the homestead from a tarred road is 27km, with standard deviation of 36km. This is a highly skewed distribution, with extreme cases on the right, pushing both the mean and the standard deviation up. A detailed examination shows that the 95th and 99th percentiles are 100km and 175km respectively.

Demographic information for the key informants in the qualitative survey is presented in table 2.2. In addition to basic demographic information, the informants were asked how many years they had been in their current positions. Informants were also asked how long they had been stationed at their current locations, or camps in the case of camp officers and blocks in the case of block officers. This information is also important as it shows the level of experience or knowledge respondents have on agricultural and local contextual issues.

Table 2.2: Demographic information of key informants

Variable	Obs	mean	sd	min	max
gender (% of Males)	23	39			
age	23	45.8	7.2	31	54
years in current position	23	14.7	8.2	5	31
years in current location	23	7.5	5.9	1	21

The sample seems biased towards females, with males accounting for fewer than 40% of the interviewed officers. Ages ranged from 31 to 54, with an average of about 46 years. The average number of years in one's position was 15, with a lowest and highest of 5 and 31 years respectively. A tabulation of the highest level of education, not shown here, shows that 11 (47.8%) of informants held certificates, 5 (21.7%) had diplomas and 6 (26.1%) had university degrees or higher. Only one (4.4%) key informants had secondary school certificate as their highest level.

2.5.1.2 Ownership of farming assets

Besides demographic information, table 2.3 shows the ownership of various farming assets and the social networks among farmers. These factors are important as they provide contextual

[10] Zambia's education system has 7 years of primary and 5 years of secondary education.

information on the status of farmers in the sample. The information also provides context for key explanatory variables in the results and discussion section.

Table 2.3: Descriptive statistics of selected covariates

Variable	Obs	mean	sd	min	max
Owns plough	7,930	.247	.431	0	1
Owns ripper	7,930	.032	.177	0	1
Owns sprayer	7,930	.218	.413	0	1
Owns oxen	7,930	.238	.426	0	1
o/w Number of oxen	1,876	3.60	2.9	1	54
Land owned	7,798	4.82	4.6	0	281
Land cultivated	7,798	2.32	2.38	0	45.5
Land tenure (leasehold==1) of fields	29,574	.044	.206	0	1
Any training	7,931	.709	.454	0	1
Cooperative membership	7,931	.506	.500	0	1
Women group membership	7,931	.215	.411	0	1
LSLS membership	7,931	.060	.238	0	1

Of the farmers in the sample, 24.7% owned a plough, 3.2% a ripper, 21.8% a sprayer, and 23.7% at least one pair of trained oxen. These are oxen trained for draught use and are part of the total number of cattle owned. For comparison, 34% of households owned cattle, at an average of 11 cattle per cattle-owning household.

The size of land owned averaged $4.8ha$, with 95th and 99th percentiles of $14.1ha$ and $38ha$, respectively, while the amount of land cultivated averaged $2.3ha$, with 95th and 99th percentiles of $6.5ha$ and $11.8ha$, respectively. On average, the size of land owned is about three times that of the land cultivated. The land tenure variable shows that only a small proportion (4.4%) of fields were under leasehold tenure with the remaining 95.6% categorised as customary land.

About 71% of households have members who have undergone some training or advice on at least one of the practices under consideration in this chapter. Social networks show that half of households have members belonging to farmer cooperatives, and 21% had membership in women's groups, while only 6% belonged to local savings and loans groups.

2.5.1.3 Adoption of various farming practices

Each respondent household was asked about the adoption of different farming practices including climate-related practices. The descriptive information is presented in table 2.4. For each practice, the household provided information on whether they had employed the practice in the immediate past agricultural season (2013/2014) and this is shown in column (1) of the table. Respondents also provided information on when they first implemented the practice, which is used to compute the number of years since adoption in column (2).

Households that reported having employed the practice in the 2013/2014 season were also asked if they continued to do so during the succeeding season, that is, the season during data collection (column 3). Finally, households that reported "No use" were asked if they had ever employed the practice in the past; their responses are presented in column (4) of the table.

Table 2.4: Proportion of Farmers Practising each Strategy

Practices	(1) Implemented last season	(2) Started (yrs)	(3) Continued in current season	(4) Ever practised in the past
Zero tillage (excluding chitemene*)	15.0	7.4	88.4	4.8
Minimum tillage (planting basins)	14.2	6.5	83.9	4.6
Ripping with animal draught power	12.5	8.2	92.1	2.1
Ripping with mechanical power	1.7	6.1	81.9	0.4
Crop rotation of cereals/legumes	49.3	8.9	96.5	9.5
Intercropping of cereals/legumes	12.3	8.0	90.7	5.8
Leaving crop residues in field	58.4	8.9	97.6	6.9
Using crop residues as mulch	16.0	7.7	96.4	1.6
Agroforestry	5.8	6.2	81.0	1.1
Irrigation	18.2[a]		16.6[b]	
Sample size	7,933			

* Chitemene is a *slash and burn* shifting cultivation common in Northern Zambia

[a] Proportion irrigating at least one field in 2012.

[b] Proportion irrigating at least one field in 2015

Between 12% and 15% of respondents employed the three types of MT. Crop rotation was also quite popular, practised by about half the respondent households, while intercropping was at 12%. The table shows that most households left crop residues in the field, a practice noted by Baudron et al. (2007). The average time from the year the household first introduced the practice is between 6 and 9 years for all the practices.

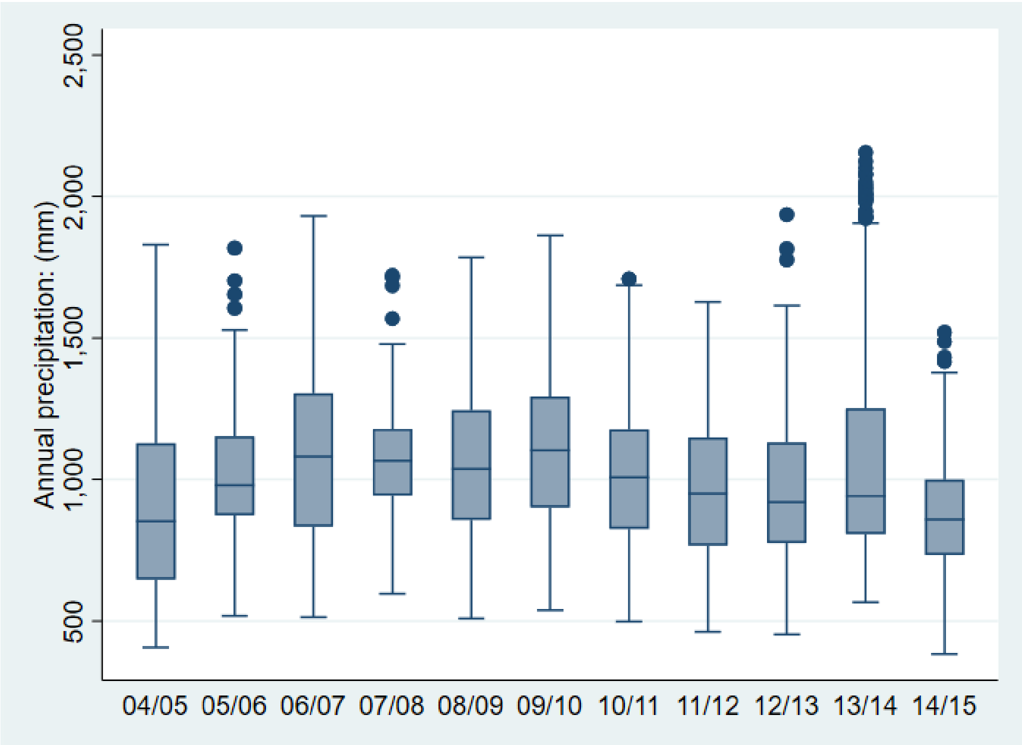
The adoption of MT suffered from high rates of dis-adoption. For instance, of the farmers who implemented zero tillage in the 2013/2014 farming season, only 88.4% continued to use the practice in the 2014/2015 season. The most cited reason for abandoning MT was, "*too risky/uncertain due to land tenure insecurity, costly labour wise*" and the feeling that the practice "*takes too much land out of crop production*". Among farmers who left crop residues in the field, almost all of them (97.6%) continued with the practice in the 2014/2015 season. As noted by Baudron et al. (2007), crop residue management is mostly a cultural issue. Farmers leave the residue in the field and allow free grazing.

The adoption of irrigation also remains low and seemingly on a decline. The proportion of farmers reporting having irrigated at least one field actually fell from 18.2% in the 2012 survey to 16.6% in the 2015 round. These results were also reported by Ngoma et al. (2017). Overall, the adoption of various climate-adaptation practices is higher than was recorded by Arslan et al. (2015) from the 2004 and 2008 surveys.

2.5.1.4 Rainfall performance

The performance of rains between the 2004/2005 agricultural season and 2014/2015 season, based on the satellite data, is shown in figure 2.1 using the box plot.

Figure 2.1: Total Seasonal Rainfall Received



The figure shows that the rainfall has been fluctuating between 2004 and 2010. The median was lowest in the 2004/05 season, rose to a high in the 2006/07 season, then dropped in the next two seasons. It peaked in the 2009/2010 season. From the 2009/10 season, it has been declining in each agricultural year. These observations were also echoed by a number of key informants:

> "The change of climate has been there, because even the rainfall pattern has changed. The rains are coming very late instead of the right time when it's supposed to be there." (CH,F)
> "it was fine and above 800mm. Recently, especially for last year, it was less than 500mm. The rains have decreased compared to some years." (CH,F)
> "Since I came in 2013, rains have been very erratic. ..., our rains season was starting mid-December, that is when we can experience serious rains, except this year when it started in November. But even though it started in November, there have been gaps, it rains maybe weekly." (CH,M)
> "There are so many changes or variations in rainfall patterns. ... The climate was okay though with occasional dry spells. But the past two farming seasons, there have been dry spells at times causing a reduction in output." (MO,F)

> ‘‘For the past 10 years, the first five years it was better but now it is getting worse. It is getting hotter and the rain is erratic. The temperatures are rising, even if it is raining, the temperature is rising.’’ (MO,F)
> ‘‘Data for the past 12 years and we can see that things are not the same. ... Most of the rains we receive is below 800 and we have a few years when we had close to 800 and a year or so when we had above 800mm. ... The amount of rains that we receive is varying. Like last year, we received about 398mm. Actually, it reached 398 because at the end of the season when the crop was already damaged, we received a good amount of rainfall. Otherwise, the whole rain season was about 273mm. ...So we can see that the distribution of rainfall has changed which is telling us that climate change is real. The temperatures are increasing, compared to previous seasons. The amount of rainfall received is reducing as we go on and they are also varying and the distribution has changed.’’ (MO,F)
>
> ‘‘There has been a change in the weather pattern. In the past years, it used to rain a lot and rains used to start somewhere in November and ending in April. But this time around, rains start late. Starting from somewhere in 2015, there was late onset of rain season and it has been ending fast. The rain season has been shortened’’ (MO,F)

The verbatim quotes above attest to the local awareness or perception of the changing climate which has resulted in decreased and erratic rainfall activities. Although this is coming out of both districts, the number of comments from Monze seems more pronounced. Of notable concern also is the changed distribution of rains, particularly the shortening of their duration. The rains not only start late, but also end early, resulting in reduced volume and duration, both of which are critical for crop performance (Guan et al., 2015).

2.5.2 Results and Discussion

The preceding subsection provided a preliminary analysis of the data. This subsection analyses the data and discusses the findings. The section tackles adaptation in four parts: Section 2.5.2.1 explores the policy and support available. The next three sections discuss different measures of adaptation: choice of adaptation strategy (subsection 2.5.2.2), diversity of adaptation (subsection 2.5.2.3), and intensity of adoption (subsection 2.5.2.4).

2.5.2.1 Adaptation policy and options

This section documents strategies that farmers are employing to adapt to increased rainfall variability, and the policies and support available, mostly based on key informant interviews and a review of policy documents.

There are a number of climate-smart agricultural practices currently being promoted and practised in Zambia. These include conservation farming (CF), crop diversification, better seed varieties with an emphasis on early maturing varieties, irrigation, and crop insurance (Arslan et al., 2014; Baudron et al., 2007; MoA and MFL, 2016). To help document camp-level strategies, key informants were asked the question, ‘‘What policies and strategies are being implemented to support smallholder farmers in adapting to climate change?’’ Respondents described all the strategies that they were promoting in their catchment areas. The responses were then classified into the major CSA practices and the frequencies of respondents mentioning each strategy are shown in table 2.5.

Table 2.5: Climate-smart agricultural practices being promoted

Practice	Mentioned by	
	Number	Percent
Conservation farming (CF)	17	73.9
Crop diversification	5	21.7
Improved varieties	6	26.1
Irrigation	4	17.4
Small livestock	4	17.4

The responses show that most respondents (74%) were engaged in promoting the adoption of CF as a response to increased rainfall variability. CF is considered the major policy response to climate change and efforts have been intensified to promote its adoption, as shown in the following comments by the informants.

> *‘‘There are a set of climate-smart agriculture technologies that we are promoting and one of them is CF.’’ (MO,F)*
> *‘‘The whole of this season, there has been a programme on radio and tv on the issue of smart agriculture, encouraging farmers to take up CF for them to have good yield.’’(CH,M)*
> *‘‘For me as a Camp Officer, I have been preaching about the very CF.’’ (MO,F)*
> *‘‘We are also encouraging our farmers in the efficient use of water in irrigation, promoting drip irrigation, growing of vegetable as a coping mechanism.’’ (MO,F)*

Other practices were mentioned by a few respondents. For instance, just over a quarter were promoting the use of improved or suitable seed varieties, often early maturing varieties,[11] while 21.7% mentioned crop diversification which is promoted as a means of spreading the risk of crop failure.

> *‘‘Facilitating so that they start diversifying. When they grow maize, they grow cowpeas, kandolo [sweet potatoes]. If maize fails, at least maybe groundnuts can do better and they can survive.’’ (CH,F)*

[11] This is a yield-safety trade-off. While early-maturing varieties offer better yields under water stress, late-maturing varieties offer better yields when well watered (Katengeza et al., 2018; Waldman et al., 2017).

> *"We have intensified on crop diversification so that there is something that can tolerate this weather or climate difference." (CH,F)*

Crop diversification is often promoted alongside CF because it provides an enabling environment for the adoption of crop rotation. However, there are still major challenges to smallholder farmers diversifying from the traditional maize-growing culture. Key informants mentioned two major challenges to crop diversification, affecting mostly smallholder farmers. The first relates to the availability of certified seed for alternative crops. Most seed producers, and hence dealers, concentrate on maize seed, neglecting other crops. The key informants' comments attest to this problem:

> *"There is the issue to do with the availability of legume seeds. I can't walk into an agro-shop and buy either beans or groundnut. Usually they are in short supply. They are not readily available. So what the farmer has to rely on is recycled seed."(CH,M)*
> *"[For] cowpeas, in most cases, farmers use recycled seed. It's not that it is their wish. Even when you go on the market, there is a shortage of certified seed for legumes. Even just soybeans, it's not there. ... You find that these seed companies, their concentration is maize, maize, maize." (MO,F)*

In growing other crops, farmers are forced to rely on recycled seed, for which there is overwhelming evidence of suboptimal yield (Wineman et al., 2020). This has contributed to the *maize-centric* agriculture, with secondary repercussions on the adoption of crop rotation and food security.

The second challenge to crop diversification concerns the availability of output markets. Farmers grow alternative crops for their monetary value on the market. However, evidence points to an absence of structured markets in most rural areas for crops besides maize.

> *"Then the farmer will not grow things for the sake of growing, they will also look at [the market] .... The cereal already has a structured market, but for the legumes it's different, I may grow beans and I may not have already market to sell that beans, I may grow groundnuts, I will not have ready market for that. So why should I grow it at a large scale despite being told the benefits?"(CH,M)*
> *"[Farmer] always talk about available markets for other crops. They know that maize, they can sell to FRA or briefcase buyers. But if one wants to maybe grow a 4 hectares of groundnuts, where would they find the market for groundnuts? Those are the issues coming out from the field."(MO,M)*
> *"We saw a lot of farmers still going back to maize .... Of course you can't really blame them, the issues of market. Farmers ... can grow anything as long as they have an assured market. Because of issues of markets, you find them involuntarily going back to maize production."(MO,F)*

The government food reserve programme is mostly centred on maize, and there are no reliable private buyers of other crops, save for a few crops like tobacco, cotton and soybeans which have dedicated buyers. Most other legumes, such as groundnuts and common beans, rely on private small-scale traders for their market (Mofya-Mukuka and Shipekesa, 2013).

Although irrigation is considered critical in the response to increased rainfall variability, its adoption and support are hampered by increasingly frequent water shortages. Precipitation deficits not only cause crop failure, but have also led to non-availability of surface water, the main source for irrigation among smallholder farmers. There are also cases where irrigation is banned in order to conserve the limited water supply for livestock, as is evident from the comment below.

> *"The level [water] was very low, some of them were even told to stop [irrigation] so as to reserve water for the animals. ... A lot of people are discouraged because the fear is that water may run dry midway of irrigation and forced to stop midway."(CH,M)*

The evidence implies that irrigation is not always a feasible option, especially for smallholder farmers, the majority of whom rely on surface water (Akayombokwa et al., 2015). In extreme cases, droughts have also led to dried-up water reservoirs and streams. This may explain the low importance that key informants attached to irrigation.

Although this section has highlighted a number of climate adaptation strategies, the rest of the chapter will focus on the adoption of irrigation (IR) and CF principles, namely: minimum tillage (MT), crop rotation (CR) and soil cover (SC). The adoption of crop diversification will be analysed in chapter 3 from a policy perspective, while the available data do not allow for a conclusive analysis of the adoption of improved seed varieties and livestock.

2.5.2.2 Choice of adaptation strategy

This section analyses a farmer's choice to adopt or not to adopt a particular practice. A farmer makes an adoption choice on each practice in a seemingly independent manner. However, because different practices tend to complement or substitute each other, a farmer's choice concerning one may not be completely independent of the adoption status of other practices (Kassie et al., 2013; Mulwa et al., 2017). Farming practices may be adopted in a correlated manner. Therefore, a multivariate or SUR probit in eqn. 2.19, based on Zellner's (1962, 1963) SUR model, is preferred to standard probit models. The SUR model has the advantage of dealing with potentially correlated disturbance terms and is also efficient compared to the standard probit (Wooldridge, 2010, p. 595).

The estimation is performed at plot-level and provides an opportunity to examine plot or field characteristics in the decision to adopt various adaptation strategies. The post-estimation table of the correlation coefficients matrix Σ from the SUR probit regressions at plot-level is given in table 2.6. This table is important as it shows the presence or absence of correlation in the disturbance terms, which fortifies the choice between the SUR model and standard probit models.

Table 2.6: Correlation matrix based on SUR probit regressions in table 2.7

	MT	CR	SC
CR	-.015		
SC	-.005	-.003	
IR	-.002	-.017	.055**
LR test	$\chi^2(6) = 6.79495$,		p = 0.3402

There is a significant positive correlation between SC and irrigation. This means fields that are irrigated are also likely to have SC implemented. This might reflect the practice of mulching in garden nurseries, a common feature of gardening and irrigation, or that farmers are more conscious of conserving water on irrigated crops than on rain-fed crops. However, the likelihood ratio test for the significance of the pairwise correlation coefficients fails to rule against the null of zero correlations. The results point to the low tendency of implementing many practices on the same plot. While farmers may adopt many practices, this finding implies that farmers seldom implement them on the same plot, negating the potential complementary benefits of multiple practices.

The results of the SUR probit regression are shown in table 2.7. The four columns relate to the four practices: MT, CR, SC, and IR, respectively.

There is a marginal influence of gender on the adoption of CR, with male domination in the household positively affecting plot-level adoption of CR. The probability of adopting MT on a given plot increases with the age of the head of household, albeit at a decreasing rate, with a turning point at about age 60. This finding is consistent with Chompolola and Kaonga (2016), who noted that age increases exposure to technologies and environments and the accumulation of physical and social capital, which increase adoption. But beyond a certain level, age is associated with lost energy, increased aversion to risk, and shorter planning horizons, which do not favour adoption of new technologies, as has been observed by a number of studies (Kassie et al., 2013; Teklewold et al., 2013a).

The level of education in the household has a negative impact on the adoption of CR but a positive impact on SC. Household size increases the adoption only of CR, but has an insignificant effect on other practices. Larger households are more likely to commit more land to cash crops, allowing the practice of crop rotation with the staple crop.

Remoteness has a negative impact on the adoption of CR and SC at both the household and plot level. Remoteness may be associated with limited access to information and other support services which may be a major influence in the adoption of new farming practices. This is consistent with *a priori* expectations.

Ownership of specialised implements, particularly rippers, has a significant impact on MT and

Table 2.7: Regression results for plot-level adoption of farming practices

VARIABLES	(1)	(2)	(3)	(4)
Dependent variable[1]	A_MT	A_CR	A_SC	A_IR
gender (males=1)	-0.036 (0.102)	0.084* (0.049)	0.052 (0.055)	-0.148 (0.177)
age	0.002 (0.001)	-0.002*** (0.001)	0.001 (0.001)	-0.002 (0.002)
education	-0.003 (0.008)	-0.016*** (0.004)	0.014*** (0.005)	-0.003 (0.014)
household_size	-0.008 (0.011)	0.005 (0.005)	0.001 (0.007)	0.008 (0.026)
distance_tarmac	0.000 (0.001)	-0.002*** (0.000)	-0.001** (0.000)	-0.000 (0.001)
asset ownership				
_plough	-0.249*** (0.077)	0.001 (0.028)	0.016 (0.034)	0.047 (0.083)
_ripper	1.044*** (0.079)	0.100** (0.042)	0.113* (0.068)	-0.025 (0.158)
_sprayer	0.234*** (0.056)	0.259*** (0.031)	-0.102*** (0.032)	0.046 (0.077)
_cattle_number	-0.007** (0.003)	-0.005*** (0.001)	0.000 (0.002)	0.002 (0.002)
_land_hectarage	-0.030*** (0.011)	0.002** (0.001)	-0.002 (0.002)	0.003* (0.002)
attended_training	0.357*** (0.058)	0.146*** (0.026)	0.014 (0.029)	-0.036 (0.076)
SID	0.158 (0.106)	1.397*** (0.056)	-0.022 (0.065)	-0.038 (0.177)
farmer category				
_B	-0.079* (0.043)	-0.003 (0.022)	0.000 (0.027)	-0.112 (0.086)
_C	0.034 (0.053)	0.040 (0.030)	-0.005 (0.034)	0.203** (0.089)
membership				
_cooperative	-0.073 (0.046)	0.084*** (0.024)	0.029 (0.027)	0.084 (0.069)
_lsls	0.215*** (0.071)	-0.028 (0.040)	0.152*** (0.048)	0.164 (0.129)
R_minus	0.023 (0.021)	-0.013 (0.008)	-0.049*** (0.012)	-0.018 (0.020)
R_minus_1	0.007 (0.023)	0.036*** (0.012)	0.062*** (0.015)	-0.016 (0.028)
year_2015	0.631*** (0.071)	-0.029 (0.033)	-0.438*** (0.052)	0.159* (0.090)
plot characteristics				
_hectarage	-0.020 (0.018)	0.047*** (0.008)	-0.006 (0.009)	-0.050* (0.027)
_distancee_homestead	-0.004 (0.006)	-0.006* (0.003)	-0.005 (0.003)	0.006 (0.009)
_dambo	0.128** (0.054)	-0.162*** (0.035)	-0.096** (0.037)	0.318*** (0.082)
_flood_prone	-0.036 (0.045)	-0.209*** (0.024)	0.032 (0.030)	-0.155** (0.073)
_tenure	-0.173** (0.081)	0.043 (0.050)	0.082 (0.060)	-0.102 (0.133)
Constant	-2.399*** (0.165)	-0.402*** (0.092)	-0.239** (0.115)	-2.290*** (0.258)
Observations	36,757	36,757	36,757	36,757

SEA clustered robust standard errors in parentheses : *** p<0.01, ** p<0.05, * p<0.1

[1] A_j=1 if adopted the practice and 0 otherwise.

CR. This expected, given that a ripper is designed for MT. The ownership of a sprayer also has a positive impact on MT and CR, but a negative impact on the adoption of SC at household level. MT is associated with the use of herbicides (Brown et al., 2018; Grabowski et al., 2014), which require the use of sprayers. Ownership of a sprayer also encourages the cultivation of crops such as cowpeas or cotton, which are suitable for rotation with cereals but susceptible to pests and diseases (CFU, 2007, p. 33).

Households that own more cattle are less likely to adopt MT and CR. With more animal draught power, the household is more inclined to conventional tillage and monocropping the staple crop, which has the effect of suppressing the adoption of CR. Training or farmer orientation shows a consistently significant impact across all farming practices. This finding is important as it highlights the importance of agricultural extension services to the adoption of new farming technologies. The results are consistent with findings from other studies (Habanyati et al., 2018; Lalani et al., 2017; Pedzisa et al., 2015b).

Both category B and category C farmers (larger farm sizes than category A) are more likely to adopt CR. This is evident at both the household and plot levels. Farmers with more land tend to grow more cash crops, such as soybeans and cotton, which permit rotation with cereals. In addition, crop diversification is positively associated with the adoption of all practices at a household level, and with MT, CR and SC at a plot level, with a visibly high coefficient on CR. Crop diversification allows the cultivation of crops that may require different levels of tillage, thus departing from the traditional intensive tillage associated with maize. More importantly, crop diversification has a remarkable influence on the adoption of CR. As noted earlier in subsection 2.4.3.10, crop diversification is the basis upon which crop rotation thrives (Kassie et al., 2013; Pedzisa et al., 2015b). In addition, the culture of monocropping was heavily cited as a hindrance to the adoption of CR by most key informants.

Membership in farmers' groups, such as cooperatives and loans and savings groups, generally increases the chances of adopting CF based principles but not irrigation. Similar results were found by Teklewold et al. (2013a) in Ethiopia and Zulu-Mbata et al. (2016) in Zambia. Farmers' groups provide a platform for the receipt of extension and support services, and for the sharing of knowledge and vital community resources among farmers. These have the effect of encouraging the adoption of new farming technologies.

The field size or hectarage has a marginally significant positive impact on the adoption of CR but a negative one on the adoption of irrigation. Irrigation levels still remain low and are often restricted to very small portions of land (Akayombokwa et al., 2015; Ngoma et al., 2017). Farmers are less likely to irrigate large fields.

Farmers are also less likely to implement any of the CF principles on fields that are far from the homestead. In Kassie et al. (2013) and Zulu-Mbata et al. (2016), distance to plot was found to have a negative effect on the adoption of CF-related practices such as CR and SC. Teklewold et al. (2013a) found similar results and concluded that distant fields tended to receive less attention and farmers tended to apply new and beneficial technologies to nearby fields.

The location of a field in a wetland/dambo area has a negative impact on the adoption of CR and SC but a positive impact on the adoption of irrigation. Not many crops are tolerant to dambo or wetland conditions, therefore limiting the practice of CR. Irrigation is driven by the location of a field in a dambo area. It was mentioned in Akayombokwa et al. (2015) that irrigation in Zambia is mainly practised in low-lying wetlands or dambo areas. It was also highlighted by a number of key informants that irrigation is still restricted to surface water, either along streams or in dambo areas.

Fields that are prone to flooding are less likely to be crop-rotated. Nonetheless, there is evidence of adoption of SC. SC is important for its role in minimising soil erosion, which is often exacerbated by floods. This result may indicate that farmers are taking proactive steps to minimise soil erosion through the adoption of SC in flood-prone fields.

The impact of rainfall extremes depends on how the rainfall shock is defined and measured. When defined as standardised deviations, based on eqn. 2.26a, there is no significant contribution. However, when the shock is defined by negative deviations, that is, measuring standardised precipitation deficits using eqn. 2.26b, there is a positive, contemporaneous effect on MT and CR. This indicates that farmers respond to exposure to rainfall deficits by adopting MT. This was also found by Kassie et al. (2013), Ngombe et al. (2014), and Zulu-Mbata et al. (2016), and a number of key informants were also of the view that farmers are quick to adopt MT when they experience the effects of droughts or dry spells.

Exposure to rainfall deficits reduces the probability of practising CR and SC. Farmers respond to threats of droughts by concentrating on maize, at the expense of CR. One key informant stated that, ‘‘they [farmers] just concentrated on maize immediately they received early rains. Most of them planted maize than other crops.’’ Further, droughts also lead to less pasture, which increases the pressure of livestock on crop residue (Arslan et al., 2015). A few key informants' opinions are worth citing:

> *‘‘I think it can be easy for them to adopt because they can see the effects of climate change now unlike in the past whereby we were telling them to do CF.’’ (CH,M)*
> *‘‘Some farmers have started adopting [MT], after seeing the weather pattern.’’ (CH,F)*

These results show that exposure to climate extremes especially dry spells and droughts, is a significant contributor to adaptation decisions. There is a reluctance among farmers to adapt until they experience extreme rainfall events, as can be seen from the following comments by key informants:

> *‘‘It's very difficult to appreciate CF when there is abundant rains and it's all good because they are harvesting.’’ (CH,F)*
>
> *‘‘Challenges to adoption include behavioural aspect. Farmers take agriculture as a tradition and can't adopt new methods.’’ (CH,M)*
>
> *‘‘Because when you tell the farmer, “can you change from this to this”, they say, “No, I have been doing this for a long time. What can you tell me, I know everything.’’ (CH,F)*
>
> *‘‘Others will say, this is what our forefathers have been doing and they have been harvesting.’’ (MO,M)*

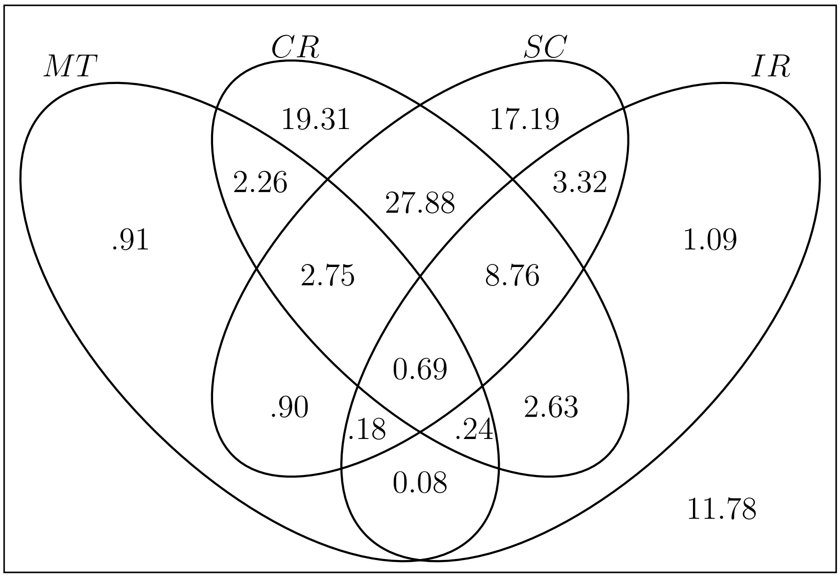
These comments give an indication of farmers' inertia in adopting new technologies and underscore the importance of information sharing through extension services.

The results also show that irrigation is driven, not so much by farmer characteristics or abilities, but by field characteristics. The results strongly suggest that irrigation is driven by the location of the field near a source of surface water, mainly dambos or wetland.

2.5.2.3 Diversity of adaptation

As argued earlier in the literature section of this chapter, adaptation to increased variability in climatic variables and adoption of various farming practices is not always a binary decision. Farmers adopt farming practices incrementally, from one practice to many in a gradual or stepped manner (Andersson and D'Souza, 2014; Baudron et al., 2007; CFU, 2012), ultimately having a diverse portfolio of practices. This section analyses factors that influence the diversity of adaptation or, more specifically, the number of practices adopted. To illustrate what farmers are adopting, figure 2.2 is a *Venn* diagram showing the percentage of farmers who adopted different combinations of the four practices.

Figure 2.2: Venn Diagram of Strategies Adopted



Very few farmers (0.69%) were practising all four climate adaptation strategies. About 19.3% and 17.2%, respectively, practised CR and SC in isolation, while 27.9% were implementing only those two. Only 2.75% of respondents had adopted full CF, comprising MT, CR, and SC. About 11.8% of respondents were not implementing any of the four practices.

Further to the information in the Venn diagram, we compute, for each farmer, the number of practices a farmer reported employing in the season under review. There are four strategies under consideration and a farmer will report having adopted anywhere between zero and four, inclusive. A zero means that farmer has not adopted any strategy or new farming practice. The number of practices is then regressed using an ordered probit model from eqn. 2.21. The regression results are given in table 2.8. Column 1 of the table is the ordered probit of the number of practices adopted by all the farmers. Columns (2-4) run the same regressions on the three categories of farmers, category A cultivating less than 2 *ha* of land, category B cultivating between 2 and 5 *ha*, and category C cultivating between 5 and 20 *ha*. The disaggregation will show any differential effects on the different categories of farmers.

In column (1) of the table, the results show that male-dominated households, on average,

Table 2.8: Regression results for household-level diversity of adoption

VARIABLES	(1) All	(2) Cat_A	(3) Cat_B	(4) Cat_C
Dependent variable	No. of practices	No. of practices	No. of practices	No. of practices
gender (male=1)	0.095* (0.054)	0.039 (0.081)	0.143 (0.095)	0.090 (0.115)
age	-0.003 (0.005)	-0.008 (0.007)	-0.007 (0.008)	0.014 (0.010)
education	0.007** (0.004)	0.005 (0.006)	0.004 (0.006)	0.012 (0.007)
household_size	0.010* (0.006)	0.024** (0.012)	0.015 (0.012)	-0.003 (0.009)
distance_tarmac	-0.001*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.001 (0.001)
asset ownership				
_plough	0.016 (0.027)	0.007 (0.057)	0.044 (0.043)	-0.026 (0.046)
_ripper	0.512*** (0.066)	0.934*** (0.244)	0.634*** (0.133)	0.446*** (0.080)
_sprayer	0.272*** (0.029)	0.440*** (0.061)	0.223*** (0.046)	0.225*** (0.045)
_cattle_number	0.000 (0.001)	-0.005** (0.002)	0.000 (0.002)	0.002 (0.001)
_land_hectarage	-0.000 (0.001)	-0.001 (0.002)	-0.001 (0.002)	0.002 (0.002)
attended_training	0.188*** (0.024)	0.170*** (0.036)	0.230*** (0.042)	0.151*** (0.050)
SID	1.542*** (0.047)	1.680*** (0.070)	1.396*** (0.085)	1.477*** (0.093)
farmer category				
_B	0.069*** (0.025)			
_C	0.112*** (0.029)			
membership				
_cooperative	0.135*** (0.022)	0.095*** (0.036)	0.104*** (0.037)	0.230*** (0.044)
_lsls	0.097** (0.048)	0.187** (0.093)	0.126* (0.076)	0.005 (0.083)
R_minus	-0.030*** (0.007)	-0.026** (0.012)	-0.030** (0.012)	-0.036*** (0.014)
R_minus_1	0.011 (0.008)	0.020 (0.014)	0.019 (0.015)	-0.016 (0.016)
year_2015	-0.197*** (0.028)	-0.092** (0.046)	-0.212*** (0.047)	-0.343*** (0.053)
Observations	11,378	4,418	3,930	3,030

SEA clustered robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

adopt more practices than female-dominated households of similar characteristics. This is consistent with the prior expectations that men often have more access to information and communal resources, and tend to possess more capital than females (Chompolola and Kaonga, 2016; Pedzisa et al., 2015b), and therefore are more disposed to adopt new technologies. There is no evidence that age plays a role in the number of practices adopted.

Ownership of farming implements has a significant positive impact on the number of practices adopted. These results are consistent with prior assumptions. Specialised implements, such as rippers and sprayers, are hypothesised to encourage adoption of more practices. Zulu-Mbata et al. (2016) also noted the role of access to implements in the adoption of CF. However, farmers with excess land tend to adopt fewer practices.

The receipt of training or extension services and membership in farmers' groups have positive impacts on the number of practices adopted. These findings are consistent with other studies. In particular, Abdulai (2016) noted the importance of extension services, social networks, and access to credit in driving the adoption of CF in Zambia. Extension services and social networks provide the technical knowledge and resources needed to appreciate new technologies.

The coefficient on SID is also highly significant. This means farmers growing diverse crops are more likely to adopt many practices than farmers who cultivate a limited number of crops. Farmers in categories B and C (more land cultivated) tend to adopt more practices than category A farmers. Exposure to rainfall deficits is associated with a reduced number of practices adopted. This is counter-intuitive. Nonetheless, there is some plausible explanation from key informants. When there are droughts, farmers concentrate on maize, therefore abandoning crop diversification which promotes crop rotation (CR). In addition, late planting due to intermittent early rains does not allow MT because the land is overgrown with weeds.

An examination of the last three columns of table 2.8 reveal important differences between the three farmer categories. The gender and educational influences only appear in category C farmers. Higher-category farmers seem to be more likely to be self-reliant and utilise their own abilities than lower-category farmers, whose abilities get overshadowed by peer learning and influence. For these reasons, the impact of the gender of the household head and the level of education are more pronounced among category C farmers.

The impact of the number of adults in a household, assumed to be a proxy for labour availability (Gollin, 2014; Pedzisa et al., 2015b), is insignificant among higher-category farmers. This implies that higher-category farmers are less constrained on labour as they can afford to hire it. Similarly, the negative impact of distance from a tarred road does not extend to category C farmers, as these are able to invest in other means of communication and transport, and therefore are able to attenuate the negative effects of living far from amenities.

The coefficients on rainfall shock show the coefficient and the level of significance increasing with the category of farmers. Farmers in higher categories are more responsive to rainfall shocks than lower-category farmers. These results seem to suggest that lower-category farmers are more constrained in their ability to adapt or change farming practices in response to rainfall shocks.

Overall, the results in table 2.8 highlight factors that matter in the adoption of more climate-resilient farming methods. While other studies (Chompolola and Kaonga, 2016; Habanyati et al., 2018) noted the importance of draught power or ownership of cattle, these results show that it is the ownership of farming implements, such as a plough, ripper or sprayer, that matter. The ownership of draught cattle may be complementary or a prerequisite. Training or farmer orientation in different farming methods also consistently promotes the adoption of more practices.

Membership in farmer organisations has significant effects on the adoption of additional practices. These organisations play an important role in helping farmers adopt new farming technologies. Firstly, cooperatives are a medium through which government subsidies are delivered (MoA, 2012, 2013a, 2018a; MoA and MFL, 2016). Secondly, farmers' groups provide a platform for peer learning among farmers, as was promoted in the conservation agriculture scaling-up project (CASU) (Kuntashula and Nhlane, 2018). Lastly, farmer organisations also provide a communication structure for the effective implementation of extension services.

There is also evidence that farmers are showing signs of responding to rainfall calamities, particularly rainfall deficits. However, this seems to be hampered by a lack of capacity to adapt adequately. For instance, a lack of complementing farming implements limits the extent to which farmers can adopt different climate-resilient farming practices. There are significant differences in response among farmers of different categories.

2.5.2.4 Intensity of adoption

The intensity of adoption is important to understand the level, depth, or degree of adoption of farming practices. To help illustrate the measurement of intensity, consider the case of the adoption of MT. A farmer is assumed to own k fields and the hectarage of each is known to be h_{ij}, where i denotes the household and $j = 1, \dots, k$ denotes the field. In respect of each crop field, a farmer indicates the tillage method used, which is categorised as MT or conventional, based on the definition in subsection 2.4.3.1. The farmer also indicates the proportion of the field p_{ij} on which the tillage method was used. The total hectarage under MT is given by:

$$H_i^{MT} = \sum_{j=1}^{k} p_{ij} h_{ij}. \tag{2.28}$$

H_i^{MT} will be zero if the household did not adopt the practice, that is, MT in this case. The proportion of land under MT for each household is then calculated as a ratio of H_i^{MT} to total hectarage:

$$P_i^{MT} = \frac{H_i^{MT}}{H_i}, \tag{2.29}$$

where H_i is the total hectarage of household fields. The same procedure is used on other practices to compute P_i^{CR} for crop rotation, P_i^{SC} for soil cover, and P_i^{IR} for irrigation.

It would also be interesting to look at an aggregated measure, the cumulative proportion of land under any practice. That is, land on which any of the practices is implemented as a proportion of total land cultivated. However, this is not practical given the data available. While respondent farmers indicated the proportion of land on which each strategy was implemented, there is no indication how those proportions relate and the degree to which they overlap. For instance, if a farmer applies MT on half the field and CR on half the field, it is not clear whether the two halves cover the entire field or the two practices are implemented on the same half. Therefore, only practice-specific intensities are presented and discussed.

The computed intensities allow us to distinguish not only adopters from non-adopters, but also possible partial adopters from full adopters. Farmers are then categorised into three categories for each practice: those that did not implement, those that implemented on part of their land, and those that implemented on all their cultivated fields. This information is important for policy-making in order to understand the status of farmers, especially those who adopt. In table 2.9, we present a tabulation of the four practices into the three categories. The table is similar to table 2.4 in the descriptive analysis subsection. The numbers differ because table 2.9 has aggregated some practices which are listed individually in table 2.4. In addition, table 2.9

is based on the answers by the respondent on each field while table 2.4 is based on the overall impression by the respondent farmer.

Table 2.9: Different stages of adoption

Practice	Adoption in 2012 (n=8668)			Adoption in 2015 (n=7748)		
	No	Partial	Full	No	Partial	Full
cat_MT	96.68	2.45	0.88	86.95	10.25	2.80
cat_CR	36.85	44.52	18.63	34.00	49.59	16.42
cat_SC	30.69	29.71	39.61	46.35	28.56	25.09
cat_IR	82.00	17.40	0.60	83.49	15.71	0.80

Table 2.9 shows that while a proportion of farmers had taken on different farming practices, very few are implementing them on all the cultivated land. For instance, while about 13% of farmers had adopted MT, only 2.8% had switched completely to MT in 2015. Similarly, while two-thirds had practised crop rotation, only 16% were rotating crops on all the cultivated area.

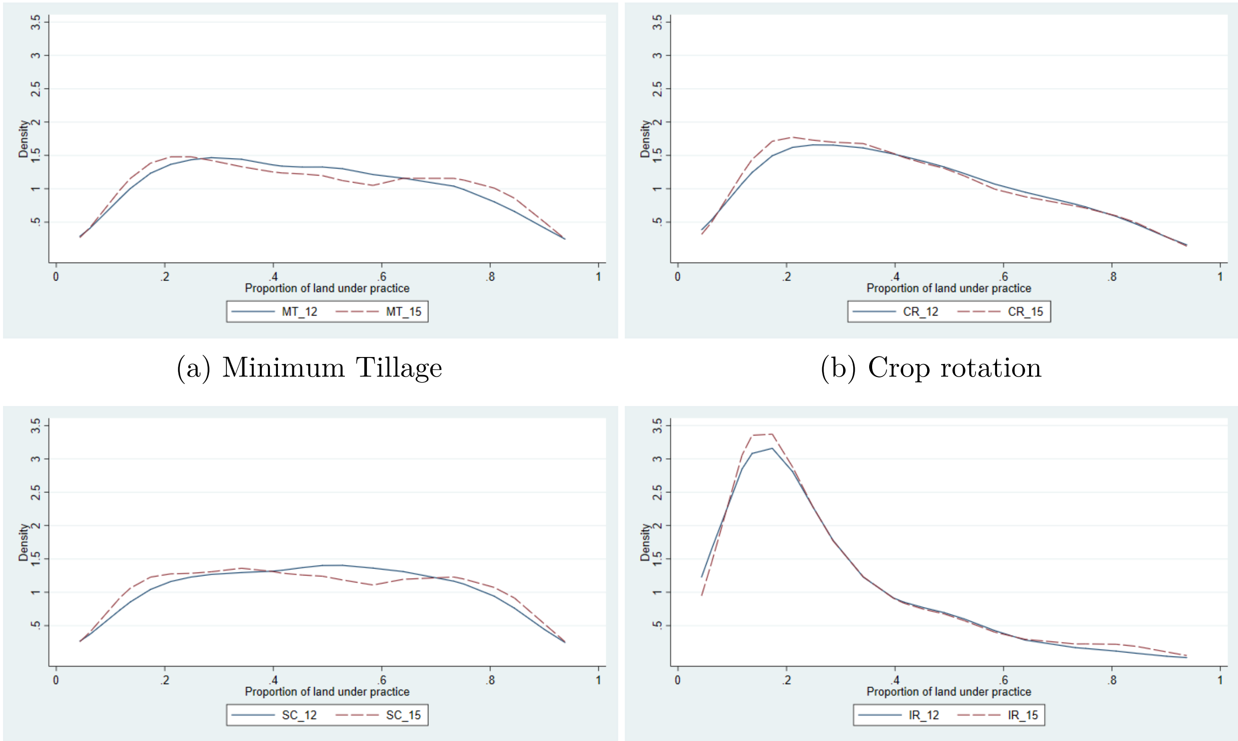
The situation is even worse for irrigation. While more than 16% reported having irrigated their fields in 2015, fewer than 1% were irrigating all their fields. A comparison across the two waves shows a slight shift towards full adoption of MT, while farmers are moving towards partial adoption for CR. The table also shows that there was some dis-adoption of SC and irrigation between 2012 and 2015.

Further to table 2.9, kernel densities are computed for all the four practices under consideration, excluding the end points. The end points, zero and one, have large deposits of observations which would distort the kernel distributions. The generation of kernel densities was conducted according to the following procedure: first a kernel density of the intensity of MT is computed using the *Gaussian* kernel with estimation points or bins $n = 50$ and a default bandwidth. The procedure is repeated with the other three practices, using the same kernel, estimation points, and bandwidth generated for the MT density. The densities are presented in figure 2.3, on identical scales. The figure provides a pairwise comparison between the 2012 and 2015 distributions.

The intensities of MT and SC seem to have shifted from unimodal (2012) to bimodal. This may imply that the intensity is shifting towards the two extremes of full and no adoption. The figure also shows a close match between the densities of MT and SC. This is not odd, as minimal disturbance to the soil also facilitates SC. Crop rotation has slightly higher frequencies around the mode and its right tail falls off faster than the other two components of CF. Irrigation seems highly peaked at less than 20% of the land. The tail going right is much thinner compared to other practices. This implies that most farmers who engage in irrigation do so on relatively smaller portions of land. There is a moderate increase in the heap around the mode in 2015.

To examine determinants of the intensity of adoption, a pooled fixed effects tobit regression model in eqn. 2.25, in line with Kankwamba et al. (2018) and Papke and Wooldridge (2008), is run for the proportion of land under each farming practice on the Xs, which include farmer

Figure 2.3: Kernel distribution of Intensity for partial adopters



(a) Minimum Tillage

(b) Crop rotation

(c) Soil cover

(d) Irrigation

characteristics, receipt of training, and exposure to rainfall shocks. The results are presented in table 2.10, where the dependent variables are proportion of land under minimum tillage (p_MT), crop rotation (p_CR), soil cover (p_SC) and irrigation (p_IR), respectively.

The results show that male-dominated households tend to irrigate larger proportions of land than comparable female-dominated households. The age of the head of household is insignificant across all the practices. The level of education in the household has a positive impact on the intensity of all but CR. The household size is associated with higher intensities of MT and CR. With more family labour, a household can comfortably increase the hectarage of cash crops, which provide a basis for the adoption of CR.

Similarly, category B and C farmers have higher intensity of CR than the category A farmers. Larger farmers grow higher proportions of cash crops, some of which may be suitable for rotation with maize, such as soybeans and cotton. The intensity of SC and IR declines with higher categories of farmers.

The index of crop diversification (SID) is positively related to the intensity of MT and CR. Some crops may not require as much intensive tillage as maize, which explains crop diversification being positively associated with intensity of MT. The results on CR are in line with prior expectations. Crop diversification provides a basis for the practice of crop rotation (Kassie

Table 2.10: Regression results for intensity of adoption

VARIABLES Dependent variable[1]	(1) p_MT	(2) p_CR	(3) p_SC	(4) p_IR
gender (male=1)	0.042 (0.062)	0.005 (0.018)	0.022 (0.037)	0.054*** (0.016)
age	0.012 (0.011)	-0.003 (0.003)	-0.006 (0.006)	-0.003 (0.002)
education	0.018** (0.009)	-0.016*** (0.003)	0.026*** (0.005)	0.004** (0.002)
household_size	0.042* (0.022)	0.015** (0.006)	-0.007 (0.014)	-0.004 (0.005)
farmer category				
_B	-0.090 (0.057)	0.033** (0.016)	-0.024 (0.033)	0.000 (0.013)
_C	0.125** (0.064)	0.096*** (0.018)	-0.075** (0.037)	0.024* (0.014)
SID	0.814*** (0.108)	1.257*** (0.032)	-0.174*** (0.063)	-0.028 (0.025)
distance_tarmac	0.000 (0.001)	-0.002*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
asset ownership				
_plough	-0.171*** (0.058)	0.012 (0.016)	-0.243*** (0.034)	0.026** (0.013)
_ripper	0.544*** (0.144)	0.043 (0.038)	-0.013 (0.074)	0.008 (0.026)
_cattle_number	-0.005* (0.003)	-0.001* (0.001)	-0.001 (0.001)	0.001*** (0.000)
_land_hectarage	-0.002 (0.003)	0.002** (0.001)	0.002 (0.002)	0.001* (0.000)
attended_training	0.487*** (0.065)	0.147*** (0.016)	0.018 (0.032)	0.062*** (0.014)
membership				
_cooperative	-0.031 (0.049)	0.049*** (0.014)	0.058** (0.029)	0.030*** (0.011)
_lsls	0.239*** (0.089)	-0.030 (0.030)	0.216*** (0.062)	0.042* (0.022)
R_minus	0.008 (0.019)	-0.017*** (0.005)	-0.060*** (0.009)	-0.029*** (0.004)
R_minus_1	-0.033 (0.024)	0.036*** (0.006)	0.072*** (0.012)	-0.003 (0.004)
R_minus_2	-0.237*** (0.025)	0.020*** (0.005)	-0.058*** (0.011)	0.015*** (0.004)
year_2015	1.615*** (0.296)	0.072 (0.074)	-0.972*** (0.147)	-0.074 (0.052)
Constant	-3.538*** (0.414)	-0.342*** (0.112)	1.182*** (0.224)	-0.357*** (0.085)
Observations	10,868	10,868	10,868	10,868

SEA clustered robust standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

[1] p_j is the proportion of land under the practice. *See* eqn. 2.29

et al., 2013; Pedzisa et al., 2015b), as noted earlier in subsection 2.4.3.10. In addition, a number of key informants cited low crop diversification as the major hindrance to the intensity of crop rotation. The following statements from key informants are worth noting:

> *"Then crop rotation also, monoculture is also high." (MO,F)*
> *"Usually, legumes they plant small areas compared to cereal crops. So now to rotate cereal crop where a legume was, it can't fit properly." (CH,M)*
> *"They prefer planting, a big area they plant maize and a small area they plant legumes, a combination of legumes they plant it in the other side." (CH,F)*
> *"You find that the maize portion is very big and for groundnuts very small. So next year, you find it will not balance. They don't have equal portions of land to balance with maize. Farmers are concentrating much on maize." (CH,M)*
> *"The legumes are done on a smaller piece. They don't do it on a big field." (MO,F)*
> *"Crop rotation, they do but it's minimal because they don't grow big fields of legumes. They would have maybe 5 hectares of maize and maybe just 2Lima [$2lima \approxeq 0.5ha$] of groundnuts." (MO,F)*

The results therefore confirm the above observations, that the intensity of crop rotation is being limited by disproportionately small portions of land being committed to crops other than maize. As farmers diversify or increase the proportions of other crops, the intensity of crop rotation also increases.

Very remote farmers have low intensities on all but MT. Remote farmers have limited access to essential information and support services for the adoption of new farming technologies. Ownership of implements such as a ripper has a positive influence on the intensity of MT, consistent with prior expectation. Farmers with more cattle tend to have low intensity on all the practices.

Training does enhance the intensity of adoption of all practices, except for an insignificant coefficient on SC. Key-informant evidence shows concerted efforts to promote the adoption of CF. Our results show that farmers who attended some training tended to implement the new practices on a much larger proportion of their fields. Trainings or extension services help farmers to realise the benefits of the new farming technologies.

Membership in farmers' groups produces varying results. This may be due to the varying orientations, objectives and approaches of different groups. Although these groups serve to promote peer learning, some do specialise in particular areas of agriculture. For instance, there are groups that will only deal with irrigation and not other aspects of agriculture. The chapter is unable to disaggregate this due to limited data.

The results show that there is less CR, SC, and irrigation when there is a rainfall deficit. There is evidence from key informants that threats of droughts cause farmers to concentrate on maize, the staple crop. This has the effect of diminishing the intensity of CR as farmers diversify less. In addition, droughts also put pressure on the use of crop residue for animal feed, reducing its alternative use as soil cover. While irrigation may be a natural response to droughts, severe droughts have actually led to the drying up of surface water, the major source of irrigation water for smallholder farmers. In some cases, local/traditional authorities have had to ban irrigation in preference to conserving water for livestock.

The prior expectation was that farmers exposed to climate extremes would be more likely to adopt these practices as an adaptation measure. There are plausible explanations from key informants of why this was not necessarily the case. The intensity of MT, for instance, is said to be partly hampered by weakened animal draught power due to depleted pastures in periods before the onset of the farming season. As conservation-based MT ought to be done before the onset of rains, as opposed to conventional tillage which is performed after the onset of rains, farmers are not able to begin MT because they depend on animals that do not have enough strength because of the lack of pasture. A few key informants explained this:

> *"They have seen it's real, they have no option but to do away with conventional farming to go to CF. The animals were weak, finished. Towards ripping time, animals were weak, such that they could not go and rip in the field because there was not enough grass, not enough water and unfortunately when that first rain came,*

most animals again died.'' (MO,F)

''Water for livestock, grass for livestock are a problem. So you find that when rain season come, the cattle are very weak because they had no food.'' (MO,F)

''We didn't have grass and water and the main draught power here is cattle. If you look at the state in which the animals are, it is pathetic. Even if today the rains come, the animals don't have the energy to till.'' (MO,F)

While farmers may be inclined to adopt MT in response to rainfall deficits, the deficits also create an inhibiting environment by affecting the main source of draught power. When the rains finally come and animals have gained some strength, MT is no longer tenable because of weeds which have overgrown the fields. The use of herbicides also remains low among smallholder farmers (Mutale et al., 2017). Consequently, farmers choose to use conventional thorough tillage, in order to remove weed overgrowths.

Drought also affects CR adoption as farmers respond to threats of droughts by prioritising maize, the staple crop. When the rains are low, farmers will make every effort to grow maize, at the expense of other crops. As a result, they are less likely to provide other crops that can be rotated with the staple crop. The practice of SC is hampered by two drought-related factors: First, cover crops are not well developed because of droughts. Secondly, because of lack of pastures, animals depend on the crop residues for food and farmers have a trade-off between retaining residues in the field and using them for stock feed, (Baudron et al., 2007), as the key informants point out:

''Even if they leave those residues, you find that during the dry season, everything is eaten up.'' (CH,M)
''Residue retention in the field, because animals have little to eat, they also utilise the same residue.'' (MO,M)
''When it comes to residue retention, it is difficult because of the animals. Animals can almost clean up the whole field.'' (MO,M)

The above quotations highlight challenges that are faced, especially in years of rainfall deficits. While farmers may be inclined to practice residue retention, their purpose is defeated by other practices, such as free cattle grazing, that are common among smallholder farmers (Baudron et al., 2007).

2.6 Conclusion

This chapter contributes to the literature on climate adaptation in general and in the Zambian context in particular. The chapter used a combination of household survey, satellite rainfall, and key informant data to address questions on adaptation strategy choice and depth of adoption.

The chapter notes that rainfall patterns have changed, increasing the occurrence of droughts and shortening rainfall periods. KII data have shown CF as the main adaptation strategy that is being promoted. Despite the changed climate and the promotion of adaptation strategies, the chapter finds that the level of adoption of CSA practices is still low, with pronounced levels of dis-adoption. In particular, the adoption of MT and irrigation remains low, at around 15% and 17%, respectively.

The econometric models show that farmers adopt MT and CR in response to precipitation deficits and to training. However, these efforts are hampered by a low adoption of complementary practices such as crop diversification and the use of herbicides. The analysis shows that the level of crop diversification is low due to the lack of available certified seed and of structured output markets for alternative crops, entrenching the culture of maize-monocropping. In order to enhance climate adaptation and improve resilience among mostly poor farming households, there is a need to improve markets for alternative crops. This is important in order to promote crop diversification, which has partly been hampered by absence of structured markets for alternative crops. Other drivers of adaptation include ownership of specialized implements and membership in farmer cooperatives or associations. This calls for the scaling up of agricultural extension services that provide necessary skills and knowledge for the adoption of new farming practices, including the use of herbicides.

On the other hand, the results show that the adoption of SC is driven mostly by the farming culture. The adoption of the practice is hampered by the free grazing practices in traditional farming communities and the need to break pest cycles by burning crop residues. Irrigation, on the other hand, seems to be driven by plot-level characteristics, mainly whether the field is in a dambo (wetland) area. This is because of the upfront costs of investment, which farmers can seldom afford. As such, there is a need to promote access to irrigation resources by smallholder farmers.

CHAPTER 3

ESTIMATING THE IMPACT OF THE REFORMS OF THE FARMER INPUT SUPPORT PROGRAMME ON THE ADOPTION OF CROP DIVERSIFICATION AND ROTATION PRACTICES

Chapter Abstract

This chapter employs a treatment effect approach to evaluate the impact of the reforms to Zambia's Farmer Input Support Programme (FISP) on household-level crop yield, crop diversification, and the adoption of crop rotation. The reforms include the introduction of multiple crops and the electronic voucher input delivery system The chapter combines a two-wave panel of rural household survey data, high-resolution satellite rainfall data, and primary qualitative data from in-depth interviews with key informants to provide answers to questions around the effectiveness of the reforms in promoting the adoption of climate-smart agricultural practices.

The chapter finds that the introduction of the electronic voucher may have caused a decline in maize yield, as farmers channel resources to other crops or agricultural ventures. However, there is no evidence that the introduction of multiple crops improved yields of supported crops. The multiple crop reform nonetheless, positively impacted on both the level of crop diversification and intensity of crop rotation. The electronic voucher on the other hand is insignificant on crop diversification, but has a significantly positive impact on the intensity of crop rotation. On the overall, the reforms were effective in stimulating the adoption of climate-smart farming behaviours. The impact is undermined by the absence of complementing services, such as functioning private sector input and output markets and the entrenched culture of monocropping.

3.1 Introduction

Conservation Farming (CF) was adopted as an official government policy in Zambia in 2000 (MoA, 2001). The government and cooperating partners have since been promoting the adoption of different principles of CF, especially among smallholder farmers, as a climate adaptation strategy. As part of this drive, the government has been reforming the Farmer Input Support Programme (FISP) in order to promote the adoption of new farming practices, among other objectives. The reforms have included, *inter alia*, the addition of other crops in the FISP and the introduction of the electronic voucher system. These reforms allow farmers to access an expanded array of inputs. This was seen as a major step in encouraging crop diversification and accelerating the adoption of the crop rotation principle of conservation farming.

Crop diversification helps minimise climate-related crop failure, as different crops will tolerate different weather conditions, in addition to providing a more balanced source of human nutrition, especially in rural settings where consumption is tied to own production (Arslan et al., 2014; Feliciano, 2019; Kankwamba et al., 2018; Tessema et al., 2015). Crop rotation, especially with legumes, allows an optimal use of soil nutrients as different crops reach nutrients at different depths, while the inclusion of legumes enhances nitrogen in the soil, and helps improve soil quality (Koppmair et al., 2017; Tilman et al., 2002).

In the literature, the promotion of crop diversification and the adoption of crop rotation are often considered as peripheral. Many studies of farm subsidy programs (Asfaw et al., 2017; Carter et al., 2014; Chibwana et al., 2014; Xu et al., 2009) have concentrated on evaluating the programmes' impacts on the primary objectives, such as crop yield, fertiliser use, and poverty in general, ignoring potential spill-over effects such as the impact on the adoption of climate-related farming practices (Jayne and Rashid, 2013). For instance, Chibwana et al. (2014) found a significant impact of Malawi's farm input subsidy programme on the intensity of fertiliser use, while Carter et al. (2014) concluded that subsidies have a persistent impact on fertiliser usage.

Although the secondary effects of reforms are important, few studies (Kankwamba et al., 2018; Koppmair et al., 2017) have looked at these. In particular, Koppmair et al. (2017) noted that a subsidy programme is a good avenue for promoting adoption of conservation farming practices, while Kankwamba et al. (2018) found subsidy programmes to have a positive effect on the degree of crop diversification among farmers in Malawi. Others, such as Jayne et al. (2018b), argue that subsidy programmes either have had no effect on the adoption of climate-smart agricultural practices or have reduced their use. This suggests that there is no consensus in the literature on how subsidy programmes impact the adoption of climate-related farming practices. The lack of consensus may be due to spatial variations in key agricultural determinants such as the microclimate or farming cultures, which many studies fail to control for (Jayne et al., 2018b). The mixed results also underscore the need for more localised empirical studies that would take into account the prevailing agro-climate, farming systems, and other key variables.

This chapter contributes to the literature on impact evaluation and climate adaptation by evaluating the impact of FISP reforms on crop yields, household-level crop diversification, and the adoption of crop rotation among smallholder farmers. In particular, the chapter will evaluate the impact of the inclusion of other crops, under FISP reforms and the introduction of the electronic voucher (e-voucher) system, on the yield of maize and groundnuts, for which there is a sufficient number of observations in the data, the degree of crop diversification (CD), and the intensity of crop rotation (CR) at the household level. In this chapter, CD refers to the cultivation of multiple crops in each season (Feliciano, 2019; Kankwamba et al., 2018) and crop rotation is defined as the alternation of crops cultivated on the same land during successive cultivation cycles (Florentin et al., 2010; Kassam et al., 2019). This definition of crop rotation downplays the requirement for the inclusion of legumes which is emphasised in the Food and Agriculture Organisation's (FAO, 2019) definition. The chapter employs a mixed-methods approach: a quantitative approach using data from nationally representative household surveys and a qualitative approach using in-depth interviews of agricultural extension workers.

The chapter attempts to address the following research questions:

- How has the reform of FISP impacted the yield of maize?
- What is the impact of new FISP on newly supported crops, particularly groundnuts?
- What has been the impact of FISP reform on the degree of crop diversification among smallholder farmers?
- What has been the impact of FISP reform on the adoption of crop rotation among smallholder farmers?

3.1.1 Objectives

The objective of this chapter is to determine the impact of FISP reforms on smallholder farmers' adoption of climate-related and sustainable farming practices. The chapter will address the following specific objectives:

- To estimate the impact of FISP reforms on the yield of maize;
- To estimate the impact of FISP reforms on the yield of newly introduced crops, with specific reference to groundnuts;
- To estimate the impact of FISP reforms on the degree of crop diversification;
- To estimate the impact of FISP reforms on the adoption of crop rotation.

3.1.2 Relevance of the chapter

This chapter is relevant for a number of reasons. Firstly, there is a general lack of conclusive evidence on the secondary benefits of government programmes such as FISP and the reforms that they introduce. Many studies (Asfaw et al., 2017; Carter et al., 2014; Chibwana et al., 2014; Xu et al., 2009) have concentrated on evaluating FISP on its primary objectives, such as its impact on crop yield, fertiliser use, and poverty in general, ignoring potential spillover effects such as its impact on the adoption of climate-related farming practices. The few studies that do address these questions (Kankwamba et al., 2018; Koppmair et al., 2017) have not provided conclusive evidence on how reforms would impact climate adaptation in general.

Secondly, this chapter introduces a measure of FISP dependence in the model and objective measures of farm-level exposure to rainfall shocks. FISP dependence has the potential to exacerbate or attenuate the responsiveness of farmers to FISP reforms. Similarly, rainfall outcomes or shocks have the potential to affect farm-level decision making and responses to FISP reforms. Other factors that add to the contribution of this chapter include better measures of demographic information in a household which take into account the role of other members of a household, as noted by both Anderson et al. (2017) and Zepeda and Castillo (1997). In particular, the chapter measures gender on the basis of the proportion of males in the household and education based on the highest level of education in a household. The chapter also is able to make use of a rich and unique data set comprising a two-wave, nationally representative household survey, detailed district level FISP allocation data, and high resolution satellite rainfall data. The household survey data have the advantage of including both pre- and post-reform observations which allow for the isolation of the impact of FISP reforms on outcome variables.

Finally, the chapter will provide empirical evidence on the role of FISP reforms in enhancing the adoption of sustainable agricultural production strategies amidst rainfall variability. The chapter will also provide information on how the reform of FISP, which aims, *inter alia*, to create resilience to rainfall variability, has impacted crop yield, CD and adoption of CR, and CF in general. As FISP continues to be reformed, this chapter will also provide insight on how further reforms are likely to impact the adoption of crop rotation and other CF principles as the country strives to build a climate-resilient agricultural system.

The rest of the chapter is organised as follows: Section 3.2 provides some brief background on FISP, section 3.3 reviews the literature and section 3.4 develops the methodology. The analysis of data and discussion of findings are presented in section 3.5 and section 3.6 presents the final conclusions to be drawn from this chapter.

3.2 Background

Since the adoption of conservation farming (CF) as an official government policy, a number of institutions have been helping farmers to adopt this new farming technology. These include the now-defunct Conservation Agriculture Scaling-Up project (CASU) under the Ministry of Agriculture (MoA)[1] (Zulu-Mbata et al., 2016). The CASU project provided technical support to promote the adoption of CF. Other institutions are Golden Valley Agriculture and Research

[1] For easy reference, this chapter uses the Ministry of Agriculture (MoA) throughout even when there were changes in the nomenclature. *See* note 1 on page 23.

Trust (GART), providing the technology necessary to support CF adoption (Arslan et al., 2014; Haggblade and Tembo, 2003), and the Conservation Farming Unit (CFU), provides CF extension services (Andersson and D'Souza, 2014; Arslan et al., 2014). There are also private companies that have supported the adoption of CF, such as Dunavant Cotton company through its contract farming schemes (Baudron et al., 2007; Grabowski et al., 2014). Faith-based organisations and/or NGOs, such as the Catholic Diocese of Monze, or the Development Aid from People to People (DAPP) (Baudron et al., 2007; Haggblade and Tembo, 2003), have been providing mainly farming input support and extension services to farmers.

Alongside these efforts, the government started to reform the FISP, first expanding the catalogue of supported crops and then introducing the electronic-voucher (e-voucher) input delivery system, with the aim of supporting crop diversification (CD) and the adoption of crop rotation (CR) in order to strengthen climate resilience among smallholder farmers. This section will discuss some of the background to the FISP (subsection 3.2.1), the reforms (subsection 3.2.2), the importance of CD and CR (subsection 3.2.3), and the theory of change showing how FISP reforms impact the adoption of CD and CR (subsection 3.2.4).

3.2.1 Farmer Selection into FISP

The selection of farmers, the quantity of inputs provided, and other modalities of FISP are set out in annually produced FISP implementation manuals (MoA, 2012, 2013a, 2016, 2018a). For the period under review (2011-2015), the programme targeted 900,000 smallholder farmers, out of an estimated 1.47 million smallholder farmers in the country (CSO, 2016b, 2017). Each benefiting farmer was allocated one indivisible pack. For maize inputs, a pack comprised $10kg$ maize seed, $100kg$ of basal dressing fertiliser and $100kg$ top dressing fertiliser. To be eligible, the implementation manuals (MoA, 2012, 2013a, 2016, 2018a) stipulated that a farmer must belong to a cooperative or a farmer organisation and cultivate between half a hectare and two hectares of maize.

Benefiting farmers are selected through their cooperatives or farmer organisations and Camp Agricultural Committees (CACs) (Mason et al., 2013). CACs are comprised of both elected farmers' and traditional authorities' representatives and a government-employed Agricultural Extension Officer (AEO). Each farming season, farmer organisations receive applications from members and recommend them to the CAC for approval based on their allocated quotas. Anecdotal evidence suggests that farmer organisations recommend eligible members on first-come basis. When selected, a farmer is shortlisted to receive one pack, for which he/she must make a *farmer contribution* upfront (MoA, 2012, 2016, 2018a). The farmer contribution depends on the level of subsidy and may vary from one year to another. In the 2013/2014 farming season, the subsidy level was 50% on fertiliser and 100% on seed.[2]

[2] In the 2013/2014 farming season, each benefiting farmer contributed $K50$ (US\$1 $\approx K5.39$ then) or the equivalent value of maize per $50kg$ bag of fertiliser as a farmer contribution.

3.2.2 FISP Reforms

While FISP had a positive effect in the promotion of maize production, it may have had an adverse effect on CD and the adoption of CR, both principal parts of CF (Andersson and D'Souza, 2014; Jayne et al., 2018a; Umar et al., 2012). In addition, Zambia is agro-ecologically diverse, from low-rainfall regions in the south-east to high-rainfall regions in the north and north-west (Jain, 2007). Some of the regions may not be suitable for maize production but more appropriate to other cereal crops such as rice, which suits paddies, flood plains, or wetlands (Behnke et al., 2018; Bhattacharyya, 2008), or drought-resistant crops such as sorghum and millet (Altieri and Koohafkan, 2008; Jain, 2007; Komba and Muchapondwa, 2018) in low-rainfall regions. This was also well acknowledged in the country's National Climate change Response Strategy (NCCRS) (MTENR, 2010) and provided impetus for CD across the country and emphasised the need for FISP to include support for other crops. The programme began a gradual reform to include inputs for other crops.

In the first year of diversification, seed and fertiliser for rice production were provided as part of FISP in the 2010/2011 farming season in selected districts. In these districts, farmers had the option of receiving maize or rice inputs (MoA, 2010), but not both. While the addition of rice could lead to increased CD, it is unlikely to encourage the practice of crop rotation. As noted by Styger (2014), rice production in Zambia is mainly in floodplains and *dambo*[3] systems, which other crops such as maize cannot tolerate. This creates a spatial separation of the rice crop from other crops, maize in particular. This kind of reform therefore cannot be considered here as constituting a catalyst to propel the adoption of crop rotation.

Sorghum (*Sorghum bicolor*), cotton (*Gossypium hirsutum*), and groundnuts (*Arachis hypogaea*) were added to the FISP in the 2012/2013 farming season in selected districts (Mason et al., 2013; MoA, 2012). Sorghum was intended to be an alternative to maize inputs. Farmers in sorghum-recipient districts would get either a pack of maize inputs, defined earlier in subsection 3.2.1, or a pack of sorghum inputs comprising $5kg$ seed, $100kg$ basal and $50kg$ top dressing fertiliser. Cotton[4] and groundnuts,[5] on the other hand, were given as additions to the pack of either maize or sorghum and farmers were given one but not both (MoA, 2012). Figure B.1 in appendix B shows the districts that received inputs for each of the three additional crops in the 2013/2014 farming season.

The introduction of additional crops was part of the CD drive aimed at accelerating CD and promoting the adoption of the crop rotation practice as farmers would grow multiple crops to rotate on their fields (MoA, 2016). Cotton and groundnuts are grown in conditions similar to maize and belong to different families of crops, making them suitable for a beneficial rotation with maize (Thierfelder and Wall, 2010).

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[3] A dambo system is a lowland system prone to excessive wetness or flooding.

[4] A cotton pack comprised $10kg$ seed and $100kg$ basal dressing fertiliser.

[5] A groundnuts pack consisted of $20kg$ seed and $50kg$ basal dressing fertiliser.

The FISP has continued to reform, with the introduction of the *electronic-voucher* input delivery system. Under this system, the government provides participating farmers with electronic vouchers[6] that they redeem with farming inputs of their choice from participating agro-dealers and shops. The e-voucher system was initially planned to be piloted in ten (10) districts. However, with the splitting up of districts and the creation of new ones, which added 6 districts to the original 10, the pilot was implemented in effectively 16 districts out of the 104 ones existing at the time. These are Chibombo, Chisamba, Kabwe, Kapiri-Mposhi, Mumbwa, Ngabwe, and Shibuyunji in the Central province; Ndola in the Copperbelt province; Chongwe in Lusaka province; and Chikankata, Choma, Kalomo, Mazabuka, Monze, Pemba, and Zimba in the Southern province (MoA, 2013b; Siame et al., 2017). These districts are highlighted in sub-figure (d) of figure B.1 in appendix B. Districts were selected for the e-voucher pilot partly because of their proximity to main highways and the 'line of rail'. This was meant to take advantage of existing communication and transport infrastructure that is conducive to private sector participation in the input distribution and supply under the e-voucher system (MoA, 2013b).

The introduction of the e-voucher system was intended to achieve a number of broad objectives including: (1) reducing public expenditure, especially on the delivery of inputs; (2) encouraging the participation of the private sector in the agro-input market and hence improving the efficiency of the supply and distribution of inputs; and (3) providing farmers with the freedom to choose inputs or crops, and promoting diversification both in terms of crop mix and a shift to other farm enterprises, such as livestock or aquaculture (Kuteya and Chapoto, 2017). The e-voucher system expanded the choice of crops for farmers in the selected districts so as to include not only a variety of crops, but livestock feed and medicines, fish feed and fingerlings (MoA, 2013b). It is envisaged that, with the inputs of many crops redeemable, farmers will start to move towards crops suitable to their respective microclimates and hence improve their resilience to extreme weather events. In addition, the system is also expected to improve the degree of CD and the adoption of CR at the household level.

The e-voucher system was ultimately rolled out to all the districts in the 2017/2018 farming season. However, due to communication network limitations in some districts, and competence limitations in the usage of ICT among agro-dealers and MoA staff, among other challenges, some districts were returned to the direct input supply mode (MoA, 2018c). By the 2019/2020 agricultural season, only 382,455 out of one million targeted farmers were operating under the e-vouchers system (MoA, 2020).

Other reforms include the introduction of a mandatory *weather-indexed* crop insurance in the 2018/2019 farming season, which in the words of the Minister of Agriculture, was aimed at 'making the subsidy programme climate-smart' (MoA, 2017). Each FISP benefiting farmer

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[6] In the 2013/2014 farming season, each voucher had a face value of $K950$ (US\$1 $\approx K5.39$ then). Farmers were required to top up this amount by $K190$ (20%) up front. In the 2019/2020 farming season, e-vouchers have a redeemable value of $K2,000$. Farmers contribute $K300$ and government contributes $K1,700$ (US\$1 $\approx K13.40$ then).

is now required to make a mandatory contribution of a $K100$ premium to insure FISP crops against adverse weather conditions such as *dry spells* or *excessive rainfall.* Insurance payments are limited to the value of the FISP subsidy and are triggered when cumulative rainfall falls below $60mm$ over 20 consecutive days (dry spell) or cumulative rainfall exceeds $150mm$ over 10 consecutive days (excess rainfall). Actual payout is pro-rated to the extremity of the adverse weather conditions as monitored by satellite technology over a large area. The payment is made irrespective of the actual losses or damage an individual farmer suffers and is informed exclusively by the performance of the rains in the catchment area.

3.2.3 Importance of Crop diversification and rotation practices

With the rains becoming more erratic, CD helps farmers to hedge against unpredictable weather. Diversifying crops ensures that not all crops fail as a result of adverse weather conditions. Crops of different groups will thrive in or tolerate different weather conditions. As Feliciano (2019) argues, CD can operate as insurance against weather variability as different crops are affected differently by weather events. For instance, maize may not tolerate prolonged dry spells but cotton will.

At the national level, CD can help reduce crop failure as farmers grow crops that are suited to the local microclimate. In this regard, Zambia's climate change strategy (MTENR, 2010) encourages the diversification of crops to more drought-tolerant crops, such as sorghum, as the country is seemingly becoming more drought prone.

In addition, crop diversification helps to achieve the much needed balanced human nutrition (Kankwamba et al., 2018) at the household level. A diversified crop base ensures household-level consumption of a variety of crops even in the absence of functioning markets. There is well-documented evidence of rural areas lacking functional markets and hence consumption is often tied to own production (Arslan et al., 2014; Tessema et al., 2015). Crop diversification also provides a platform for the practice of crop rotation, discussed below.

Crop rotation is the practice of alternating crops with different characteristics, cultivating them on the same field during successive cultivation cycles (Florentin et al., 2010; Kassam et al., 2019). Crop rotation allows for the efficient and optimal use of soil nutrients, as different crops root at different depths, thus reaching nutrients at different depths (Florentin et al., 2010). In addition, crop rotation with legumes, in particular, allows other crops to benefit from the nitrogen-fixing properties of legumes (Koppmair et al., 2017; Tilman et al., 2002). Crop rotation may also help break the life cycles of crop-specific pests and diseases (Corbeels et al., 2014; Florentin et al., 2010) and conserve the soil structure (Liebman and Dyck, 1993).

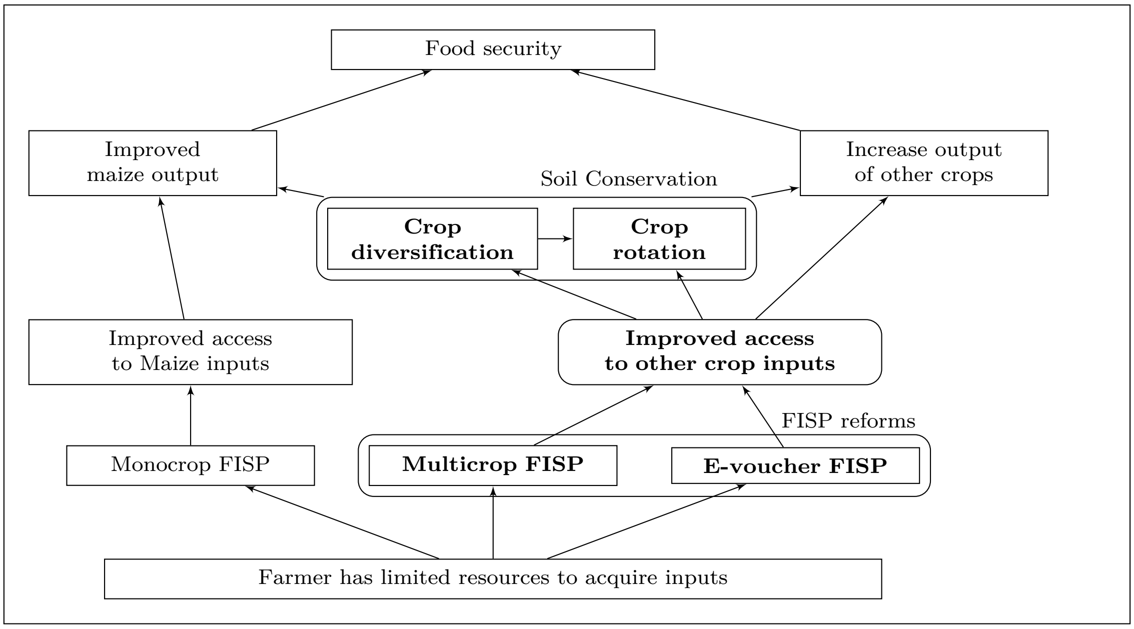
There are clearly multiple benefits to crop rotation. To a farmer, crop rotation has the potential to improve yields and to help fight pests and diseases, while also helping to improve and/or conserve the soil structure. However, the uptake of CF remains low in Zambia, mainly because of low levels of CD and the prevalent culture of monocropping of the staple crop (Andersson and

D'Souza, 2014; Habanyati et al., 2018). The CFU (2007) estimates that legumes occupy less than 10% of smallholder crops in any farming season, inhibiting full-scale rotation with cereals. Intercropping, on the other hand, remains uncommon in Zambia. It is partially practised in the high rainfall northern regions where maize is intercropped haphazardly with beans, while in other regions farmers fill gaps in maize fields with crops such as pumpkins and okra (CFU, 2007).

3.2.4 FISP reforms and the adoption of crop diversification and rotation

The reforms to the FISP programme seek, among other objectives, to improve access for smallholder farmers to the inputs of multiple crops, in order to create a diversified crop base and improve yields and climate resilience through the promotion of crops suited to regional microclimates. This would also encourage the practice of crop rotation as farmers grow more crops. A theory of change (TOC) is shown in figure 3.1.

Figure 3.1: Theory of change (ToC) for the impact of FISP reforms



Source: Author's own construction based on MoA (2012, 2013b).

In the TOC in figure 3.1, the diversification of FISP to include other crops and the introduction of the e-voucher system help improve access to inputs for other crops besides maize by mainly resource-constrained smallholder farmers. This is hypothesised to contribute to CD, both at the household and national level. The reform also provides an enabling environment for the adoption of the practice of crop rotation, a fundamental of CF. Farmers must choose from two options: crop rotation or no crop rotation. They are more inclined to choose crop rotation because it results in soil conservation and higher yields. It is therefore expected that FISP will engender greater crop rotation, but this needs to be tested empirically as "irrational" behaviour might see farmers choosing no crop rotation. Farmers may also prefer to grow staple crops on their most fertile and best cleared lands in order to make use of animal-drawn implements, as observed by Florentin et al. (2010, p71). This may have the effect of preventing crop rotation even when crops are well diversified.

3.3 Literature Review

There are not many studies looking at the secondary effects of input subsidy programmes or their reforms. A few examples exist, including Koppmair et al. (2017), who noted that FISP is a good avenue for promoting the adoption of conservation farming practices. Kankwamba et al. (2018), on the other hand, found FISP to have a positive effect on the level of crop diversification among smallholder farmers in Malawi. This section therefore provides a review of the literature on farm input subsidies and their impact on the adoption of sustainable or climate-smart agricultural practices with a view to identifying existing gaps. The section is divided into three broad areas of literature: econometric approaches in the literature (subsection 3.3.1), data issues (subsection 3.3.2), and definition and measurement of variables (subsection 3.3.3).

3.3.1 Methods in the Literature

Impact evaluations of programmes or reforms generally rely on the work of Neyman (1923) and Rubin (1974), now generally referred to as the *Neyman-Rubin* model of treatment effect (Abbring and Heckman, 2007; Rosenbaum and Rubin, 1983; Sekhon, 2010). Applications of this model have been categorised as single treatment models (Imbens and Wooldridge, 2009; Rosenbaum and Rubin, 1983; Sekhon, 2010) and multi-valued or multiple treatment models (Cattaneo, 2010; Frolich, 2004; Lopez and Gutman, 2017). The models compare the performance of an individual when given one kind of treatment and the individual's performance if not treated at all. However, this cannot be estimated due to what Holland (1986) called the fundamental problem of causal inference. That is, each individual is only observed under one group or treatment (Abbring and Heckman, 2007; Cattaneo et al., 2013; Imbens and Wooldridge, 2009; Lopez and Gutman, 2017; McCaffrey et al., 2013).

This has resulted in the use of the average treatment effects (ATE), which rely on a potential outcomes framework (Frolich, 2004; Imbens and Wooldridge, 2009; Leite et al., 2018; Lopez and Gutman, 2017). In a two-treatment model, as employed in this chapter, three potential outcomes are postulated for each individual, post-treatment: $Y_i(1)$ if the individual receives treatment 1, $Y_i(2)$ if treatment 2, and $Y_i(0)$ if not treated (control group). If all the potential outcomes were observable for each individual, the pairwise difference is the relative treatment effect. In practice however, only one outcome is observed and the others become the counterfactual.

The randomised controlled trial (RCTs) approach provides an ideal solution to dealing with the issue of the counterfactual by ensuring that the control group is a 'look-alike' of the treated group. In RCTs, the assignment to treatment and control is random and independent of potential outcomes (Imbens and Rubin, 2015; Imbens and Wooldridge, 2009; Lopez and Gutman, 2017). The assumptions of individualistic, probabilistic, and unconfounded assignment to treatment and control groups ensure that the differences in observed outcomes between the treated and control groups are unbiased measures of treatment effect (ATE and ATT).

However, the assumptions of individualistic and probabilistic assignment to treatment seldom hold in observational studies, as non-random assignment characterises most studies of this nature (Heckman, 1979; Imbens and Wooldridge, 2009; Rosenbaum and Rubin, 1983). In the present case, the assignment of farmers to different types of FISP was criteria-based and not probabilistic, and was based on district characteristics and not those of individuals. Selection into FISP treatments was influenced by district-level characteristics such as historical production of relevant crops (MoA, 2012, 2013a), proximity to major communication infrastructure such as highways, and the microclimate (MoA, 2013b), which also influence the outcome variables: yield, CD, and the adoption of crop rotation. This introduces potential endogeneity in the model. Households assigned to different treatments also have different abilities and different predispositions to agriculture and the agro-climate.

A number of methods have been suggested to deal with the potential endogeneity. These range from regression adjustment (RA), inverse probability weighting (IPW), instrumental variables (IV), Difference-in-Differences (DiD), regression discontinuity (RD), endogenous switching regressions (ESR), and matching methods mostly based on propensity score matching (PSM) or nearest neighbour matching (NNM). The RA includes potential explanatory variables in the model in order to isolate a treatment-induced difference in outcomes, while the IPW computes a weighted difference, where weights are based on each observation's probability of belonging to the treated (or control) group (Cattaneo, 2010; Imai and Dyk, 2004; Imbens and Wooldridge, 2009; Lopez and Gutman, 2017). The RA and IPW can be combined into the inverse probability weighting with regression adjustment (IPWRA), as employed in this chapter.

The IV relies on an additional layer of treatment called instruments, which have to satisfy specific exogeneity restrictions (Frolich, 2004; Imbens and Wooldridge, 2009). The IV method requires the identification of instruments that have no direct influence on outcome variables. The only influence comes through their influence on selection for treatment and the method is blind to unobserved determinants (White, 2013). The DiD provides a panel comparison of treated vs control and before vs after treatment, and is able to isolate time-invariant unobservable determinants through differencing (Frolich, 2004; Imbens and Wooldridge, 2009). Identification using DiD relies on the *parallel trends* assumption, which states that in the absence of treatment, the treated would have followed the same time trend as the control group (Fredriksson and Oliveira, 2019; Stuart et al., 2014). This assumption, however, cannot be tested in a DiD approach with only one time-point on each side of treatment. Because of a criteria-based assignment to treatment, the treated and the control groups are likely to differ even in variables that also influence their time trends in outcome variables. This introduces a selection bias across groups which is not cured by DiD alone. The RD design, on the other hand, requires many time points on at least one side of treatment (Imbens and Wooldridge, 2009) and is not applicable in the present circumstance.

Matching methods generally use the Mundlak (1978) and Rosenbaum and Rubin (1983) approaches. The approaches utilise *propensity score* and/or *nearest neighbour* matching (Sekhon, 2010). Propensity score matching (PSM) involves matching each treated unit with the nearest control unit on the basis of a propensity score, a unidimensional metric (Sekhon, 2010). In single treatment models, binary choice models are used to generate propensity scores (Arpino and Mealli, 2011; Bellio and Gori, 2003; Imbens and Wooldridge, 2009), while multinomial logit is used for generalised propensity scores in multiple treatment studies (Leite et al., 2018; Li and Li, 2019; Yang et al., 2016). The PSM is said to be the coarsest balancing score, able to control for pre-treatment covariates using a univariate score (Cattaneo et al., 2013; Imbens and Wooldridge, 2009; McCaffrey et al., 2013; Rosenbaum and Rubin, 1983). On the other hand, the nearest neighbour matching (NNM) approach assigns the unobserved potential outcomes for the control group using average outcomes of individuals with similar observed characteristics (Imbens and Wooldridge, 2009; Rosenbaum and Rubin, 1983; Sekhon, 2010). Matching methods can be done with or without replacement (Caliendo and Kopeinig, 2006, 2008; Lopez and Gutman, 2017; Sekhon, 2010). When replacement is allowed, observations in the control can be paired with multiple observations in the treated groups while matching without replacement imposes a one-on-one matching. The choice between the two is arguably a matter of trade-off between bias and variance, where replacement has a smaller bias but with larger variances (Caliendo and Kopeinig, 2006, 2008).

These methods have been employed in the literature to estimate the impact of subsidies and their reforms on different outcome variables in agriculture. For instance, Chibwana et al. (2014) estimated the impact of subsidy receipt on fertiliser usage using a general model of the form:

$$Q = \phi_0 + \phi_1 J + \phi_2 T + \phi_3 L + \mu, \tag{3.1}$$

where Q is the total amount of fertiliser used in the farming season, J is household characteristics and L represents lagged values of the dependent variable. The aggregate value of the subsidy received, considered as a treatment, is represented by T. The model has potential endogeneity because selection to FISP was informed by farmer characteristics, which also affect the outcome variable. Chibwana et al. (2014) used a *two stage least squares* (2sls) approach, using the number of years the household has been in the village and village size as instruments for treatment. Since Malawi's subsidy programme required that beneficiaries be long-time members of their respective villages, they argued that the length of stay in the village could be an instrument for subsidy receipt alongside village size. They found that receipt of a subsidy increased fertiliser use.

In addition, Chibwana et al. (2014) also looked at the impact of FISP on maize yields using a plot-level yield function of the form:

$$y_{ij} = \beta_0 + \beta_1 F_{ij} + \beta_2 H_{ij} + \beta_3 I_{ij} + v_{ij}, \tag{3.2}$$

where F_{ij} is the quantity of fertiliser used per hectare, H_{ij} and I_{ij} are dummies indicating the employment of intercropping and the use of improved seed, respectively. They found FISP to have a significant impact on the intensity of fertiliser use. They estimated that a standard FISP package, consisting of improved seed and fertiliser, would increase maize yield by about $447kg/ha$.

Koppmair et al. (2017) used a multivariate probit approach, based on Zellner's (1962, 1963) seemingly unrelated regressions (SUR) model, by looking at the adoption of a number of farming technologies and a dummy variable for subsidy receipt. Using a latent variable y_k^*, which can be understood as the net benefit from adopting a given technology, they run a SUR probit of the form:

$$y_k^* = \beta_{0k} + \beta_{1k} F + Z\gamma_k + \varepsilon_k, \tag{3.3}$$

where Z is a vector of household and regional characteristics as well as a time dummy, and F is a dummy indicating the receipt of FISP. As in the case of Chibwana et al. (2014), this model also has potential endogeneity because selection into FISP and the adoption of natural resources management practices may both be influenced by the same unobserved household characteristics (Koppmair et al., 2017). This is dealt with by using a fixed-effects approach in line with Mundlak (1978) and Wooldridge (2010, chap. 15), who prescribed inclusion of the means of time-varying explanatory variables.

Carter et al. (2014) looked at the impact of input subsidies on the adoption of inorganic fertiliser usage from the perspective of liquidity and learning. Subsidies have been noted to increase the use of inorganic fertiliser and improved seed (Asfaw et al., 2017; Xu et al., 2009). The receipt of subsidies helps farmers to access cheaper inputs, which might trigger the adoption of technology such as CF. However, the sustainability of these gains depended on sustained subsidy programmes. There is evidence that farmers opt out of these technologies when subsidies terminate (Arslan et al., 2014).

Carter et al. (2014) estimate the model of the form:

$$Y = \alpha + \beta Z + \theta + \epsilon, \tag{3.4}$$

based on the intent to treat (ITT) approach, where Y is the outcome variable indicating the use of inorganic fertiliser, Z is an indicator of receipt of a subsidy voucher, and θ is a vector of village fixed effects.

Kankwamba et al. (2018) used a simple difference-in-difference approach to estimate the effect of Malawi's FISP programme on farm-level crop diversification. They run a *two-limit tobit* model, similar to one used by Koppmair et al. (2017) in eqn. 3.3, with a strictly positive latent variable y^*,

$$y^* = X\beta + \gamma F + \varepsilon \tag{3.5}$$

where X is a vector of explanatory variables, β the corresponding vectors of parameters, and F is a dummy indicator of whether the household was a FISP recipient or not. The impact of FISP receipt is captured by γ. This framework has a potential endogeneity because FISP recipients were not randomly selected but picked on the basis of farmer characteristics which also have the potential to influence outcome variables. The authors employ the difference-in-differences (DiD) to cure systematic differences between the treated and control groups. The endogenous switching regression (ESR) model, based on Lee (1978, 1982), has also gained popularity in impact evaluations of endogenous selection to treatment. The ESR model is made of two stages or parts: the selection to treatment and the impact of treatment as in eqn. 3.6.

$$Y_{iT} = X_{iT}^{'}\beta_T + u_{iT}, \tag{3.6a}$$

$$Y_{iC} = X_{iC}^{'}\beta_C + u_{iC}, \tag{3.6b}$$

$$T_i^* = Z_i^{'}\gamma + v_i. \tag{3.6c}$$

Equations (3.6a) and (3.6b) regress the dependent variable (Y) on a vector of covariates X for farmers in the treated and control groups, respectively. The dependent variables Y_{iT} and Y_{iC} are said to be censored since only one can be observed on the same farmer (Lee, 1982). The third (eqn. 3.6c) is the *decision equation*. The latent variable, T_i^*, can be thought of as the net benefit gained from self-assigning to treatment. The model runs a simultaneous estimation of the binary adoption model and the continuous outcome models. This is analogous to the two-stage least squares in the Heckman (1979) methodology. The estimation strategy is discussed in detail by Lokshin and Sajaia (2004).

The ESR model has been extended to a model allowing for multiple values of treatment. Two versions have emerged, both based on a multinomial selection equation in place of eqn. 3.6c. The multinomial endogenous switching regressions model (MESRM) based on Bourguignon et al. (2007) and employed by Kassie et al. (2015b) and Teklewold et al. (2013b) on the impact of endogenously adopted sustainable agricultural practices. The second is the multinomial endogenous treatment effect model (METEM), based on Deb and Trivedi (2006b). This has been applied by Maggio et al. (2018) and Manda et al. (2016) on the impact of endogenously adopted sustainable agricultural practices. Multinomial endogenous models have the advantage of allowing for simultaneous estimation of selection to multiple treatments and the impact of treatment, as well as accounting for endogeneity in the selection to treatment. For multiple treatment, this chapter opts for the multinomial endogenous treatment effect (Deb and Trivedi, 2006b; Maggio et al., 2018; Manda et al., 2016). This has been described as computationally easy compared to the closely related multinomial endogenous switching regressions (MESRM) (Manda et al., 2016).

The models in equations 3.3, 3.4, 3.5, and 3.6 are very similar in the way that they treat the input subsidy. All three models follow the treatment effects approach, in which the subsidy is included as a dummy variable or a structural shifter. The potential endogeneity problem is dealt with using instrumental variables (Chibwana et al., 2014), the fixed effects approach used by Koppmair et al. (2017), the double difference method (Kankwamba et al., 2018), or instrumentation through multinomial endogenous treatment models (Maggio et al., 2018; Manda et al., 2016). This chapter argues that the measures implemented in the literature may not be sufficient to cure endogeneity problems in observational studies. Instrumental variables or fixed effects, for instance, will be blind to unobserved effects, while the efficacy of the double difference method hinges on the assumption of a common trend, which may not always hold. This chapter proposes combining the DiD and matching estimations in order to deal with unobservables and improve balance between the treated and control groups.

3.3.2 Data in the Literature

The importance of quality data in research cannot be over-emphasised. A review of data is also important in order to understand the findings generated. This subsection therefore looks at the types of data employed in the various studies on the impact of agricultural subsidies on the adoption of climate-related agricultural practices. Most studies relied on panels of nationally representative surveys of farmers or rural households. For instance, Koppmair et al. (2017) used two rounds of nationally-representative household survey data from Malawi and Kankwamba et al. (2018) also used two rounds of integrated household surveys conducted in 2004/2005 and 2010/2011.

Other studies relied on regional studies. Examples include Chibwana et al. (2014), who used a three-round panel data study from the central and southern regions of Malawi to investigate the extent to which Malawi's farm input subsidies induced inorganic fertiliser use among smallholder farmers.

Although the above studies were mostly based on rich panel data sets, they failed to utilize the pre- and post-treatment properties that would allow the isolation of the treatment effect. Pre- and post-treatment datasets allow the isolation of the treatment by pre-treatment differences in the dependent variable. This chapter will improve on this by exploiting the pre- and post-treatment characteristics of the available data.

3.3.3 Key Variables in the Literature

This subsection highlights the types of variables that are commonly used in impact evaluations of subsidies in agriculture and how they are measured. This is useful for informing the choice of variables and their measurements.

3.3.3.1 Crop performance

Crop performance is mostly measured using crop yield, defined as the amount of crop per given area, often expressed in kilogrammes per hectare (kg/ha) (Abdulai, 2016; Lalani et al., 2017). This is widely used in impact evaluations that seek to measure impact of interventions on yield, as is being attempted here (Arslan et al., 2015; Asfaw et al., 2017; Carter et al., 2014; Kassie et al., 2015a; Maggio et al., 2018). The alternative is the crop revenue, often using the net crop revenue per hectare (Di Falco and Veronesi, 2013; Jain, 2007). The net crop revenue takes into account the output produced as well as the value of inputs used. Therefore, it does account for variations in the usage of inputs, something that is lacking in the yield measure.

3.3.3.2 Crop diversification

There are two main definitions of crop diversification (CD). First, CD is generally viewed as a shift from traditionally cultivated crops to new crops (Basavaraj et al., 2016; Bhattacharyya, 2008). The change might be motivated by considerations of microclimate suitability or by the value of alternate crops. The second definition refers to the cultivation of multiple crops, often driven by the desire to spread the risk of crop failure from climate hazards (Feliciano, 2019; Fonta et al., 2018; Kankwamba et al., 2018; Maggio et al., 2018). This chapter looks at CD in the context of the latter definition.

Studies dealing with CD use the Simpson index of diversification (SID), based on Simpson (1949). For instance, Arslan et al. (2018) used the SID to estimate the degree of crop diversification at household level in Zambia. Other studies include Jones et al. (2014) and Kankwamba et al. (2018), who used the SID as a measure of CD in Malawi, while Baiyegunhi et al. (2015), Bhattacharyya (2008), and Mithiya et al. (2018) used the SID to estimate the extent of crop diversity in selected states in India. The index measures the degree to which farmers have diversified their crop base. It may be interpreted as the probability that two randomly selected fields will have different crops (Jones et al., 2014). The index, from Simpson (1949), is as defined earlier in eqn. 2.27:

$$SID = 1 - \sum_{i=1}^{n} P_i^2, \quad \text{where } P_i = \frac{A_i}{\sum_{i=1}^{n} A_i}, \tag{3.7}$$

where A_i is the area of land allocated to the ith crop. The SID will be zero if only one crop is grown and will approach one under full diversification, where a farmer grows many crops in equal proportions (Basavaraj et al., 2016; Bhattacharyya, 2008).

3.3.3.3 Crop rotation

Crop rotation refers to the practice of rotating the crops planted on each piece of land, or temporal diversification (Liebman and Dyck, 1993), with an emphasis on a mix of legumes and non-legume crops. Although this definition does not prescribe the number of seasons to consider, Andersson and D'Souza (2014) have argued that crop rotation requires a multi-seasonal definition. It is therefore common for researchers to define crop rotation on the basis of three cropping seasons (Andersson and D'Souza, 2014; Arslan et al., 2015).

The uptake of CR can be evaluated as a binary choice variable, categorised into adopters and non-adopters (Arslan et al., 2014; Grabowski et al., 2014). The major weakness of this approach is its failure to account for different levels of application of CR. There is evidence that while farmers may adopt some technology, the degree to which they apply that technology will vary (Arslan et al., 2014; Kassie et al., 2013).

Adoption of CR can also be measured in intensity by using the proportion of land under rotation, as was done earlier in chapter 2. This approach has been applied in a number of studies. For instance, Kassie et al. (2013) on the study of sustainable agricultural practices in Tanzania, Arslan et al. (2014) on the adoption of CF in Zambia, and Grabowski et al. (2014) on the adoption of minimum tillage among cotton farmers in Zambia used the proportion of land under a given practice as a measure of the intensity of adoption. The outcome variable is continuous but bound in [0,1].

3.3.3.4 Rainfall shock and/or amount

Agriculture among smallholder farmers is mostly rain-fed. As such, the rainfall outcome remains a major determinant of yield (Branca et al., 2013; Jain, 2007; Lal et al., 2001). In addition, farmers' behaviour and attitudes towards climate adaptation is influenced by their experience of rainfall patterns (Arslan et al., 2014; Kassie et al., 2013). Adverse rainfall is hypothesised to affect yields negatively and to coerce farmers to increase CD and the adoption of crop rotation. However, no studies have included objectively measured household-level exposure to rainfall shocks in modelling climate-adaptation decisions. For instance, Kassie et al. (2013) measured rainfall shocks on the basis of farmers' perceptions of the timeliness, adequacy and distribution of rains, while Arslan et al. (2014) used district-level measurement of rainfall.

3.3.3.5 Demographic variables

Demographic variables are important because they explain some of the decision-making in a household. For instance, gender disparities in the ownership of critical assets, access to information and aversion to risk have been noted to influence decision-making in a number of studies (Chompolola and Kaonga, 2016; Mulwa et al., 2017; Ragasa et al., 2013). Although studies include only the gender of the household head, Anderson et al. (2017) and Zepeda and Castillo (1997) have shown the importance of the demographics of other members in a household. Age indicates one's accumulation of experience and knowledge of production systems and hence the capacity to appreciate new technologies (Kassie et al., 2013).

Education helps improve access to and comprehension of information, as well as the capacity to adopt new farming technologies (Arslan et al., 2014; Komba and Muchapondwa, 2018).

The effect of education on yield is also well documented (Pedzisa et al., 2015b). Although traditionally the level of education of the household head is used (Kassie et al., 2013; Pender and Gebremedhin, 2008), there is growing evidence that other members of the household, such as a spouse, do influence decision-making (Acosta et al., 2019; Anderson et al., 2017; Zepeda and Castillo, 1997) and of their levels of education being equally important. This is, however, ignored in most studies of this type.

3.3.3.6 Household size

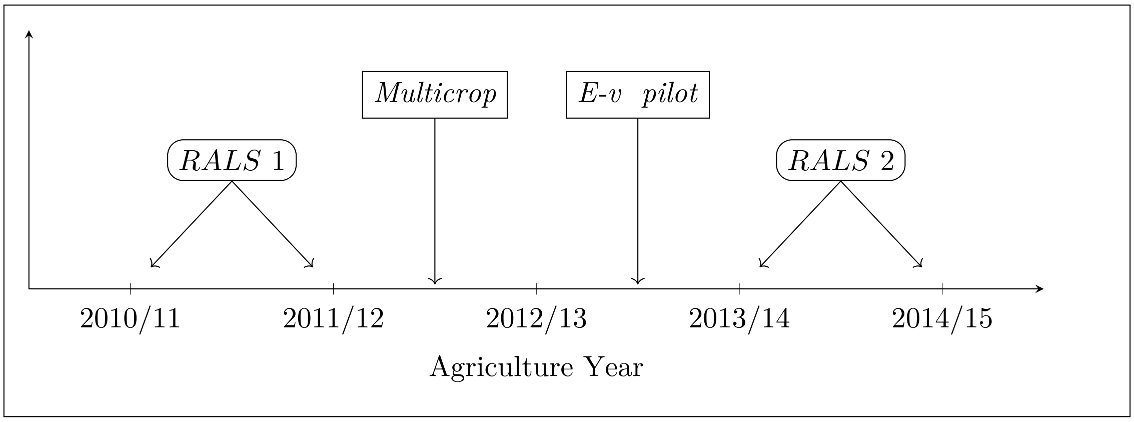
Most rural areas lack functional markets for factors of production (Arslan et al., 2018; Kassie et al., 2013; Reardon and Zilberman, 2018). Consequently, smallholder farmers mostly rely on family labour (Gollin, 2014; Pedzisa et al., 2015b). Therefore, household size is a proxy for labour availability in a farming household. For this purpose, Arslan et al. (2014) used the number of members above 15 years, while Xu et al. (2009) used the number above 14 years, as a measure of household size. The central statistical office used 12 years in agriculture-related surveys (CSO, 2014, 2017).

This chapter draws on a rich dataset which allows for the computation of all the above variables. However, the chapter has noted some weaknesses in the definition of some variables and proposes some improvements. For instance, the chapter deviates from the tradition of capturing the demographics of only the household head, as recent evidence shows the importance of other members of a household in decision-making (Anderson et al., 2017). In addition, the chapter proposes important additional variables whose impact has not been adequately examined. Existing literature implicitly assumes that the impact of a subsidy reform is uniform across all farmers. This chapter hypothesises that the impact of a subsidy on a farmer's behaviour will depend on the extent to which an individual farmer depends on the subsidy. Secondly, all the models fail to incorporate exposure to rainfall extremes, an important factor in rain-fed agriculture. This chapter improves on previous models by including objective measures of FISP dependence and rainfall in the model.

3.4 Methodology

In this chapter, baseline data on crop yield, farm land and use is collected for the 2010/2011 (and 2011/2012 on some variables) in the Rural Agricultural Livelihood Surveys (RALS). Districts, and by extension FISP recipient farmers, are then divided into three groups in the 2012/2013 to 2013/2014 farming seasons. One group continues on the traditional monocrop FISP. The other two are given the reformed FISP, which also takes two forms: multiple crops FISP, which will be referred to as treatment 1, for one group and the e-voucher system, referred to as treatment 2, for the other. The selection of farmers for the subsidy was uniform across all the districts. This is helpful for ensuring that farmers of similar characteristics and standing are selected in all the groups. The second round of RALS was then conducted on the same farmers for the 2013/2014 (and 2014/2015 on some variables) agricultural season. Figure 3.2 shows these events in a chronological order.

Figure 3.2: The Chronology of FISP Reform



source: Author's illustration

The scenario in figure 3.2 forms a natural experiment, providing pre- and post-treatment observations. The pre- and post-treatment observations allow for the control of other factors that might affect outcome variables and enables the estimation of *treatment* effects of FISP reforms at household level. A fuller discussion of the model is provided in subsection 3.4.1. The data and definition of variables are discussed in subsections 3.4.2 and 3.4.3, respectively.

3.4.1 Model Specification

The model in this chapter is based on the *Neyman-Rubin model* of treatment effect (Abbring and Heckman, 2007; Rosenbaum and Rubin, 1983; Sekhon, 2010). Each farmer is assigned to either the traditional, multicrop, or e-voucher FISP. With two parallel FISP reforms, a multivalued treatment is defined using a nominal variable in line with Frolich (2004) and McCaffrey et al. (2013):

$$T = \begin{cases} 0 & \text{if traditional} \\ 1 & \text{if multicrop} \\ 2 & \text{if e-voucher} \end{cases}, \tag{3.8}$$

and an outcome variable y representing either crop yield, CD or crop rotation. The districts are grouped into three, those who received the multicrop FISP, those that received the e-voucher FISP, and those with the traditional, maize-only, FISP. This chapter makes a bold assumption here that other interventions catalogued earlier in section 3.2 are independent of this assignment. With three (3) groups, there are three possible relative pairwise ATEs and double the number of equivalent ATTs.[7] However, not all of them may be relevant. This chapter is interested in

[7] The number of relative pairwise ATEs is given by $k(k-1)/2$ where k is the number of groups, including the control (Leite et al., 2018; McCaffrey et al., 2013).

the impact of FISP reforms and will confine itself to *estimands* comparing to the traditional FISP. All the districts are observed twice, pre- and post-treatment.

The potential outcomes from such a scenario can be presented in a 3×2 table, showing combinations of assignment to groups and time periods. The potential outcome is Y_{jt}, as shown in table 3.1, where Y represents yield, crop diversity and crop rotation, while $j = 0, 1, 2$ represents the group assignment and $t = 0, 1$ represents the pre- and post-treatment periods.

Table 3.1: Assignment to FISP type and RALS wave

		Period	
		pre-treatment	post-treatment
Group	traditional	Y_{00}	Y_{01}
	multicrop	Y_{10}	Y_{11}
	e-voucher	Y_{20}	Y_{21}

If assignment to treatment was randomised, there would be no systematic difference in the outcome variables among the three groups in the pre-treatment period, $t = 1$,

$$E(Y_{j0}) = E(Y_{00}),\ j = 1, 2.$$

With that assumption, the pairwise treatment effect would be estimated by the pairwise difference in outcomes in the post-treatment period, $t = 2$. However, selection was not random but criteria-based. The assignment of districts to treatments was informed by their respective microclimates and the potential of the private sector to distribute and supply inputs, among other factors (MoA, 2013b) which also have the potential to impact outcome variables.

The criteria-based assignment gives rise to two central problems: (1) the post-treatment differences also contain pre-treatment differences in outcomes, and (2) the treated and control groups would evolve with different trajectories (Fredriksson and Oliveira, 2019; Stuart et al., 2014). The first problem is cured by the difference-in-differences (DiD) estimation. The DiD controls the post-estimation difference with the pre-treatment differences to isolate the effect of treatment, particularly time-invariant unobservable factors (Asfaw and Davis, 2018).

For the second problem, Rosenbaum and Rubin (1983) have demonstrated that when conditioned on a set of observable explanatory variables X, the assignment can be considered unconfounded. This is sometimes referred to as *ignorability* in multiple treatments (Cattaneo, 2010). The difference, conditional on X, that is observed at $t = 2$ is attributed to the effect of the treatment. Conditional on X, the average treatment effect for the treated (ATT) is derived from Sekhon (2010) as:

$$ATT = E_X \left[E\left(Y_{11}|X\right) - E\left(Y_{01}|X\right) |T = 1 \right]. \tag{3.9}$$

In order to estimate the impact of FISP reform on the outcome variables, eqn. 3.9 is transformed to a linear regression model in eqn. 3.10, which brings in additional control variables. The regression model is given by

$$Y_{ijt} = \tau T_i + X'_{ijt}\beta + \varepsilon_{ijt}, \quad t = 1, 2., \tag{3.10}$$

where X is a vector of household characteristics including education, family size, land size, ownership of draught cattle, wealth status, and distance to major amenities including Extension Officers and markets, district averages of distances to major amenities as well as rainfall as measures of district level fixed effects. The subscripts ijt refer to household i in district j at time point t. The parameter τ will measure the average treatment effect on the treated.

In addition to the control variables in eqn. 3.10, the chapter also includes a measure for dependence on the subsidy, FD, similar to the reliance on government support used in Mulwa et al. (2017). FISP dependence can be defined as the extent to which a farmer depends on FISP for inputs. This might be related to a farmer's economic status but may bring out other aspects of interest. For instance, issues of access to input markets and the role of inter-household transfers are well captured by looking at an index of dependence on FISP. A farmer may be well-to-do economically, but lack access to the market. This is possible, especially in remote areas, and has the potential to impact on decision making (Akayombokwa et al., 2015; Arslan et al., 2014; Jayne and Rashid, 2013). Others will be poor economically but enjoying benefaction of inputs through inter-household transfers (Fink et al., 2014). In these two cases, the response to FISP will differ from what would be predicted by economic status alone.

The computation and motivation of the dependence index (FD) is detailed later in subsection 3.4.3.3. The final equation for estimation is:

$$Y_{ijt} = \tau T_{ijt} + \theta FD_{ijt} + X'_{ijt}\beta + \varepsilon_{ijt}. \tag{3.11}$$

The model in eqn. 3.11 forms the basis for the estimation of the impact of FISP reforms on yield, crop diversification and crop rotation. The analysis is performed at the household level.

To control for the criteria-based selection to treatment, the chapter employs three alternative methods: IPWRA, the METEM (ESR for single treatment) and PSM methods. The combination has the advantages of curing unobserved time invariants as well as improving the balance among comparison groups. The IPWRA and METEM also allow for the examination of other control variables which is not possible under matching estimators. The METEM is said to be computationally easy compared to the multinomial version of the ESR (Manda et al., 2016).

The PSM is run with replacement, allowing observations in the control group to be matched with multiple observations in the treated groups. Matching with replacement has been argued to produce matches of higher average quality and yield lower bias compared to matching without replacement (Abadie and Imbens, 2006; Caliendo and Kopeinig, 2006, 2008; Imbens and Wooldridge, 2009; Kuntashula et al., 2014; Lopez and Gutman, 2017). On the downside, matching with replacement leads to an unbalanced sample, having fewer observations in the control than are in the treated group(s). As noted by Abadie and Imbens (2006), the PSM is consistent even under weak regularity conditions. Although assignment to the three types of FISP which constitute treatment was based on district-level indicators, Arpino and Mealli (2011) have demonstrated that matching on district-level characteristics is not necessary. Arpino and Mealli (2011) have also provided an exposition on the specification of propensity scores in multivalued treatments, such as is the case here. Although treatment is at a household level, assignment to treatment is at a cluster (district) level.

Following Arpino and Mealli (2011), the propensity score is specified as a function of household-level characteristics. Selection to multicrop FISP was informed by the microclimate and crop suitability in various regions. For selection to e-voucher, the chapter follows the Minister's (MoA, 2013b) statement to Parliament on 5th March, 2013, which indicated proximity to highways and other supportive infrastructure as forming the criteria for the selection of districts for the e-voucher programme. The use of multiple approaches to cure selection issues ensures the robustness of the results. As argued in subsection 2.4.1 and as guided in Abadie et al. (2017), the standard errors are clustered at the standard enumeration area (SEA) level while the PSM use robust Abadie-Imbens standard errors (Abadie and Imbens, 2006).

3.4.1.1 Estimating the impact on crop performance

The impact of FISP on crop performance can be measured using a modification of eqn. 3.11. The dependent variable is modified to yield y_{ijt} and the treatment now constitutes the receipt of FISP for a selected crop. The following equation will be run to estimate the impact of FISP reform on the yields of maize and groundnuts, for which there is a sufficient number of observations in the data:

$$y_{ijt} = \tau_y T_{ijt} + \theta_y FD_{ijt} + X'_{ijt}\beta_y + \varepsilon_{ijt}. \tag{3.12}$$

The dependent variable y_{ijt} is computed as the ratio of total output in kg to area planted in hectares at a household level.

3.4.1.2 Estimating the impact on crop diversification

Crop diversification will be measured using the Simpson index of diversification approach in eqn. 3.7. The index can be computed at either hectarage or output levels. At hectarage level, the index reveals farmers actions or efforts towards diversification. When computed at output level, it shows the level of diversification in output which might differ from the former if crop failure is not independent of crop type. In this chapter, the index is computed at hectarage level, as employed by Kankwamba et al. (2018). The index is bound between zero for monocropping and near one for a perfectly diversified household. The model, similar to latent variable model in eqn. 3.11, is given by:

$$S_{ijt} = \tau_S T_{ijt} + \theta_S FD_{ijt} + X'_{ijt}\beta_S + \varepsilon_{ijt}, \tag{3.13}$$

where S_{ijt} is the Simpson index of diversification as defined earlier in eqn. 3.7 measured at the household level. X is a vector of household characteristics, such as the age and gender composition of a household, highest level of education in a household, number of adults, distance to tarmac, number of cattle owned, area of land cultivated, agricultural-related training received, and membership in farmer groups. The treatment variable T represents a multiple treatment regime, defined in eqn. 3.8. The effectiveness of FISP diversification in stimulating CD is captured by τ_S.

3.4.1.3 Estimating the impact on crop rotation

This chapter uses intensity of adoption as the measure of adoption of crop rotation. The chapter defines intensity, in line with Andersson and D'Souza (2014), as the proportion of land on which the practice is applied. It is bounded in [0,1], zero if the household does not practice any crop rotation and one if crop rotation was implemented on all the cultivated land. This is then regressed using the model of the form:

$$P^{CR}_{ijt} = \tau_P T_{ijt} + \theta_P FD_{ijt} + X'_{ijt}\beta_P + \varepsilon_{ijt} \tag{3.14}$$

where P^{CR} is the proportion of land under crop rotation, defined later in eqn. 3.16, and other variables are as defined in eqn. 3.11. The impact of FISP reform will be measured by τ_P.

3.4.2 Data

The FISP reforms under review occurred between the 2012/2013 and 2013/2014 agricultural seasons. The main data are from a two-wave panel of Rural Agricultural Livelihood Surveys (RALS), described in subsection 1.3.1. The first wave of RALS was conducted in 2012 and collected information pertaining to the 2010/2011 agricultural year. The chapter will refer to this as the pre-reform wave. In 2015, the same households were surveyed about the 2013/2014 farming seasons, which occurred after the reforms in question. As demonstrated in subsection 1.3.1, the data provide a balanced two-wave panel of 7,254 rural households. The data provide demographics, farmland characteristics, input market access and other economic variables, such as ownership of draught animals and other farming implements, and information on climate-adaptation farming practises adopted.

The chapter also includes CHIRPS rainfall data described subsection 1.3.3. The data will provide an objectively measured household-level microclimate, which is important in assessing farmer response to policy stimuli. Other data include the qualitative key informant interviews described in subsection 1.3.2 and used extensively in chapter 2. The data provide some context to the quantitative findings. In the references to qualitative data, the abbreviations 'CH' and 'MO' refer to Chisamba and Monze districts, respectively, while 'M' and 'F' identify the respondent as male or female. The assignment to treatment is based on the Farmer Input Support Programme's (FISP) allocations to districts extracted from FISP implementation manuals. These contain guidelines on how the programme is to be implemented, including farmer selection guidelines and the number of input packs allocated to each district (MoA, 2012, 2013a).

3.4.3 Operational Definitions of Variables

This subsection provides conceptual definitions of the variables as employed here and is informed by existing literature on climate adaptation and impact evaluation (Cattaneo et al., 2013; Chibwana et al., 2014; Kankwamba et al., 2018; Michler et al., 2019).

3.4.3.1 Dependent variables

This chapter has three main dependent variables: crop performance, crop diversification, and the adoption of crop rotation practices. As discussed in section 3.3.3.1, crop performance can be measured using either crop revenue or crop yield. While the former has the advantage of capturing important variables such as the value of inputs, it is in the same vein likely to suffer from spatial variations in output prices. Besides, the interventions in this chapter (FISP reforms) is one that does not have a significantly-varying impact on the cost side of production or access as standard farmer contributions and other processes apply across the treatment groups (MoA, 2012, 2013a). On the other hand, crop yield has been widely used in similar studies (Arslan et al., 2015; Asfaw et al., 2017; Carter et al., 2014; Kassie et al., 2015a; Maggio et al., 2018).

Therefore, crop performance is measured using crop yield, defined as the quantity of a crop realised from a unit area, expressed in kilograms per hectare (Abdulai, 2016; Lalani et al., 2017). This is computed at household level for each crop grown using a weighted mean of yield from each field. The weights are based on the hectarage cultivated in each crop field. The RALS data have information on all the crops that a farmer grew, the areas covered and the estimated quantity harvested. This allows the computation of yield at both plot and household level. The degree of CD is measured by the SID in eqn. 3.7 using the area covered by each crop.

This chapter considers a field or plot to have been crop-rotated if different crops were planted in the three consecutive agricultural seasons surrounding the surveys. The RALS has data on what crop was planted in each field in the season of data collection and the two preceding seasons. If at least one crop was different, the farmer is considered to have practised crop rotation on that field, without placing any emphasis on the use of legumes. The total area where crop rotation is practised is the sum of the areas from all the fields, denoted by H^{CR}:

$$H_{it}^{CR} = \sum_{j=1}^{m} p_{ijt} h_{ijt}, \tag{3.15}$$

where h_{ijt} is the hectarage of each field and p_{ijt} is an indicator of whether the field was crop-rotated or not. The intensity of crop rotation is then calculated in line with Andersson and D'Souza (2014) as the proportion of land under crop rotation to total land cultivated:

$$P_{it}^{CR} = \frac{H_{it}^{CR}}{H_{it}}, \tag{3.16}$$

where H_{it} is the total hectarage cultivated. The proportion is zero if a farmer did not rotate any crops in the fields and it is one if crop rotation was practised on all the fields.

3.4.3.2 Treatment (FISP reforms)

As discussed earlier in subsection 3.2.2, FISP reforms are in two forms and comprise the reforms of FISP, rather than FISP itself. The traditional or monocrop FISP was implemented in all the districts in the first wave of RALS. In the second wave, some districts still continued with the traditional FISP. This group of districts provides the control or untreated group. The other districts were divided into two groups. The first group received FISP which contained inputs for other crops besides maize. This forms treatment 1. A farmer is considered to have received multicrop treatment if they belonged to a district that received multicrop FISP. The other group of districts received the e-voucher FISP, which was still being piloted. This forms treatment 2 and farmers in these districts are taken to have received e-voucher treatment. Table 3.2 shows the number of districts by FISP type in the second wave of RALS.

Table 3.2: Number of districts by FISP type in 2015

Type of FISP	Number	Percent
Traditional FISP	42	40.38
Multicrop FISP	46	44.23
E-voucher FISP	16	15.38
Total	104	100.00

Each of treated districts had received only one form of the reformed FISP. Treatment is zero in the first wave for all the districts and assumes the three possible values in the second wave.

3.4.3.3 FISP dependence

FISP dependence (FD) is the degree to which a farmer depends on FISP for farming inputs. A subsidy index is defined as the ratio of the subsidy value to own income (Aveh et al., 2013; Schreiner and Yaron, 2001). This chapter therefore defines subsidy dependence as the ratio of subsidy inputs to total inputs applied. The ratio will be calculated using the number of $50kg$ bags of fertiliser a farmer used as a measure of inputs. Three reasons motivate the use of fertiliser. Firstly, fertiliser is used in a reasonably fixed ratio with improved seed and other inputs. Secondly, fertiliser is mostly supplied in standardised quality and quantity in $50kg$ bags, which makes it easy for farmers to recall and account for the quantity used. Thirdly, although farmers can use any type of fertiliser, most use the Nitrogen, Phosphorous and Potassium (NPK)

10-20-10 for basal and 46-0-0 for top dressing, especially for maize (Burke et al., 2019). Using seed might be biased by the use of recycled seed, which introduces different qualities (Thapa and Keyser, 2012). Wineman et al. (2020) have also shown that it is common in Tanzania for farmers to misrepresent recycled seed as improved seed. Therefore, the FD is defined on the basis of fertiliser as:

$$FD = \frac{Q_F}{Q_T}, \tag{3.17}$$

where Q_F is the quantity of fertiliser obtained from FISP and Q_T is the total quantity used. The index is bound in [0,1]. In the extremes, it is 1 if a farmer is wholly dependent on FISP for fertiliser and 0 if he/she did not receive FISP inputs.

3.4.3.4 Rainfall

The rainfall outcome has the potential to affect crop yield and farmer response to FISP reforms. For instance, the suitability of different crops largely depends on the rainfall pattern (Haggblade and Tembo, 2003; Jain, 2007; Xu et al., 2009). In addition, the rainfall pattern or the microclimate of different regions also played a role in the assignment of districts to different treatments. Districts were assigned to multiple crop or e-voucher FISP based on their microclimates, among other factors (MoA, 2013b). In this chapter, rainfall is measured as the sum of standardised negative deviations of each month's rainfall from the long-term average for that month $\bar{r}_{im}$ in a season.[8]

$$R_{it}^{-} = \sum_{m=1}^{12} \frac{(r_{itm} - \bar{r}_{im})^2}{\sigma_r^2}, \text{ if } r_{itm} < \bar{r}_{im}. \tag{3.18}$$

This is the second part of rainfall shock defined in eqn. 2.26 under chapter 2. The motivation to use the negative deviations only is informed by the reforms' objective of responding mainly to lower or declining rainfall activities (MoA, 2013b).

3.4.3.5 Demographic variables

As in chapter 2, age refers to the age of the head of household. Gender is measured as the proportion of males in the household and educational level is the highest level of education in the household, irrespective of whether it is attained by the household head or another member. Household size in rural agricultural households is a proxy for the availability of labour because of the absence of factor markets. We measure household size as the number of members who are above 15 years of age.

[8] In Zambia, the agricultural season runs from 1st October of one year to 30th September of the following year (CSO, 2014, 2017; Mason et al., 2013). *See* footnote 7 on page 39.

3.5 Empirical Analysis

This section analyses the data in two parts: descriptive analysis in subsection 3.5.1 and a discussion of results and findings in subsection 3.5.2.

3.5.1 Descriptive Analysis

Descriptive analysis provides information on the nature of the sample. This is important for an informed understanding of the sample and its characteristics. In this section, four important types of information are provided. These are: farmer characteristics (subsection 3.5.1.1), the acquisition and use of fertiliser (subsection 3.5.1.2), the status of dependent variables (subsections 3.5.1.3, 3.5.1.4, and 3.5.1.5), and the test for attrition bias (subsection 3.5.1.6).

3.5.1.1 Farmer characteristics

Household characteristics are important ingredients in household-level decision-making. The choices that farmers make on which farming practices to adopt are often informed by household characteristics such as size, level of education, and other human capital variables. The ownership of assets, such as draught power and implements, access to information, and social networks also all influence farmer choice because they affect the options and amount of knowledge available. It is therefore vital to gain an understanding of the farmers in the groups under comparison. Table 3.3 shows the demographic, social and economic information of the farmers in the three groups in 2012. Column (1) has all the households while columns (2-4) have the traditional (control), multicrop (treatment 1) and e-voucher (treatment 2) FISP groups. Column (5) has the difference between multicrop and traditional groups (Diff_1) while column (6) compares the e-voucher with the traditional group (Diff_2).

From the table, there seems to be significant differences in demographic information among the three groups. The age of heads of households was around 46 years, with the multicrop districts having a lower average. The proportion of males in a household was just below half and there do not seem to be any significant differences among the groups. The level of education in the household was lowest at 7.4 years in multicrop districts and highest at 8.6 years in e-voucher districts and the differences among the three groups are highly significant

The measure of remoteness was highest at 32km in the multicrop but was around 27km in the traditional and e-voucher districts. Other variables are training and land used which all seem to have different averages among the three groups of districts.

The ownership of farming assets has the potential to influence household-level decision making. For instance, the ownership of cattle serves two purposes among smallholder farmers. First, cattle are looked at as a store of value and the number owned is an indicator of the level of wealth. Secondly, cattle also provide draught power for the majority of smallholder farmers (Dibbits, 1999).

Table 3.3: Social, economic and demographic information

Variables	(1) All	(2) Traditional	(3) Multicrop	(4) E-voucher	(5) Diff_1	(6) Diff_2
age	46.2	47.15	45.46	47.28	1.69***	-0.12
gender (male=1)	0.48	0.48	0.48	0.49	0	-0.01
education	7.84	8.23	7.44	8.65	0.78***	-0.42***
household_size	3.21	3.21	3.12	3.55	0.09*	-0.34***
trained	0.69	0.56	0.71	0.82	-0.15***	-0.26***
remoteness	30.07	27	32.33	26.96	-5.33***	0.04
land_cultivated	2.48	1.88	2.51	3.41	-0.63***	-1.53***
cattle_number	3.06	2.33	2.43	6.63	-0.1	-4.30***
asset ownership						
cattle	0.32	0.17	0.33	0.54	-0.15***	-0.36***
plough	0.23	0.12	0.20	0.49	-0.09***	-0.37***
ripper	0.02	0.01	0.02	0.07	-0.02***	-0.06***
sprayer	0.16	0.07	0.16	0.32	-0.09***	-0.25***
tractor	0	0	0	0.01	0	-0.01*
waterpump	0.02	0.02	0.02	0.05	0.01	-0.03***
social networks						
cooperatives	0.47	0.34	0.52	0.52	-0.18***	-0.18***
women group	0.22	0.15	0.23	0.30	-0.08***	-0.14***
loans/savings	0.03	0.02	0.03	0.05	-0.02***	-0.03***
seasonal_rainfall	1011.72	1136.57	1000.62	839.71	135.95***	296.86***
Observations	7250	1938	4175	1137	6113	3075

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

The ownership of various farming assets seems higher in e-voucher districts than in the other districts, and seemingly increasing from traditional, to multicrop, to e-voucher districts. For instance, 17%, 33% and 54% reported owning cattle in the traditional, multicrop and e-voucher districts, respectively. The ownership of a mouldboard plough follows a similar pattern, showing that most farmers who have cattle are also likely to have a plough. As already mentioned, cattle are used for draught power and a plough is the basic implement used with cattle. This may buttress the earlier claim that FISP reforms were not independent of overall agricultural activities in the districts. The ownership of mechanised farming implements, such as tractors, remains extremely low, stressing smallholder farmers' dependence on animal power. The table shows that just over 1% of respondent households reported owning a tractor in the e-voucher districts and fewer than 0.5% in the other districts.

Membership in farmer cooperatives is 34%, 52% and 52% among farmers in traditional, multicrop and e-voucher districts, respectively. It is expected that households with membership in farmers' groups would be higher in agriculture-oriented districts because such membership is a prerequisite to access FISP inputs and the groups provide a platform for the receipt of extension services (MoA, 2012, 2016, 2018a). Membership in local savings and loan societies remains low across all the districts, at 5% of farmers or fewer. On the overall, the table shows that there are significant pre-treatment differences in demographic, social, and economic status of households in comparison groups.

3.5.1.2 Acquisition of fertiliser and importance of FISP

Access to farming inputs such as fertiliser remains a challenge for smallholder farmers. While these inputs may be commercially available, smallholder farmers can not afford the prices, which is partly the reason that FISP exists. Table 3.4 shows the major sources of fertiliser for smallholder farmers in the control and the two treated groups. The major sources are: (1) FISP, (2) cash purchases from retail outlets, cooperatives or fellow farmers, (3) retail loans, mainly from private traders, (4) loans from contract and out-grower schemes, (5) direct exchange or barter, and (6) other sources, including the food security pack. For each source, the table shows the percentage of farmers who acquired any amount of fertiliser through that source and the average quantity acquired.

Table 3.4: Fertiliser acquisition: percentage of farmers and average quantity

	Traditional				Multicrop				E-voucher			
Source	2012		2015		2012		2015		2012		2015	
	%	kg	%	kg	%	kg	%	kg	%	kg	%	kg
Number	829		923		2463		2947		871		976	
FISP	69.5	332	67.1	277	75.5	307	64.1	281	50.1	301	55.4	287
Cash purchases	45.7	396	55.0	366	45.3	420	53.9	412	70.0	614	73.3	561
Loan - retail	0.2	125	0.4	258	0.2	163	2.5	161	0.8	464	0.7	357
Loan - outgrower	0.8	621	1.1	436	1.6	429	19.7	156	1.0	456	15.3	170
Barter/exchange	0.0		0.2	175	0.2	325	0.3	457	0.6	910	0.3	308
Other	2.2	112	4.3	333	1.8	119	3.7	168	3.7	146	6.0	280

Table 3.4 shows that roughly two-thirds of smallholder farmers acquired fertiliser from FISP in traditional and multicrop FISP districts. The percentage is lower, around half, in e-voucher districts, which are dominated by cash purchases. The average quantity of fertiliser from FISP was consistently above 300kg in 2012 but fell to below 290kg in all three groups in the 2015 wave. The averages are still above the 200kg of fertiliser that was prescribed per recipient farmer in the pre-reform period and the monocrop districts (MoA, 2012, 2016, 2018a). This is possibly because some households may have more than one member registered to receive FISP inputs. In some cases, two or more farmers may, informally, share a pack. This is why some farmers reported having received less than 200kg from FISP.

Cash purchases were reported by about half of the farmers but are as high as 73% in e-voucher districts. The average quantity bought also seems higher among farmers in e-voucher districts. For instance, the average is consistently below 400kg in districts in the monocrop FISP, but is more than 500kg in the e-voucher districts in both years. Further, the average quantity in the multicrop FISP is consistently more than the average in the monocrop FISP. If cash purchases of inputs are taken as an indicator of private investment in agriculture, the average quantities across different modes of FISP may suggest that the implementation of FISP reforms was influenced by the level of agricultural activities in each district. The results suggest that there is more private investment in agriculture in districts that were selected for reform.

Very few farmers accessed fertiliser through retail loans, fewer than 1% in most cases. This is consistent with the literature, which has pointed to lack of credit in the agricultural sector in general and particularly credit that is accessible by smallholder farmers (Akayombokwa et al., 2015; Komba and Muchapondwa, 2018; Morris et al., 2007; Pedzisa et al., 2015b). Nonetheless, some credit is available through out-grower schemes or contract farming, especially among the treated groups. Out-grower and contract farming have been noted as an important form of credit among smallholder farmers (Andersson and D'Souza, 2014; Zulu-Mbata et al., 2016). There is a notable increase from 2012 to 2015 in the percentage of farmers accessing loans through in this way. For instance, 19.7% and 15.2% of farmers reported having received loans through out-grower schemes in multicrop and voucher districts, respectively, in the 2015 survey compared to 1.5% and 1.0%, respectively, in the 2012 round. The increase in out-grower schemes and contract farming was also noted by Baudron et al. (2007), working on two districts that were later included in the e-voucher FISP. The estimates may however underestimate the prevalence of this source of credit because these are mostly available for cash crops such as cotton and beans (Baudron et al., 2007; Feliciano, 2019; Grabowski et al., 2014), which do not require as much fertiliser as maize, but do require other inputs such as pesticides and herbicides.

The ratio of FISP fertiliser to total fertiliser used is also important to show the relative importance of FISP to farmers. The ratio of FISP fertiliser to total fertiliser applied is measured using the FISP dependence ratio defined earlier in eqn. 3.17. The descriptive statistics of the FISP ratio are shown in table 3.5.

Table 3.5: Ratio of FISP to total fertiliser used

Type of FISP	2012					2015				
	obs	mean	sd	min	max	Obs	mean	sd	min	max
Traditional	828	0.602	0.451	0	1	923	0.538	0.445	0	1
Multicrop	2,463	0.633	0.432	0	1	2,946	0.483	0.436	0	1
E-voucher	871	0.371	0.436	0	1	976	0.359	0.405	0	1

The ratio has an average of around 0.5, with high standard deviations. There are some reductions in the ratio, especially for the traditional and multicrop districts, but an increase in the e-voucher districts. The table also shows that the ratio is lower in e-voucher districts. This is consistent with earlier results from table 3.4, where it was noted that there were more cash purchasers in e-voucher districts. Further examination shows that there are many corner cases. This is not odd, given that about a third of farmers are not benefiting from FISP, justifying many zeros. There are also many resource-constrained FISP beneficiaries who depend solely on FISP inputs.

3.5.1.3 Crop yield

Crop yield is defined as the quantity of a crop in kilograms per hectare of cultivated land. This section looks at the crop yields of selected crops, particularly those supported by FISP. While the e-voucher FISP can be used to redeem the inputs of any crop, this subsection looks at crops that are supported under the multicrop FISP.

Table 3.6 shows plot-level crop yields of the four crops, maize, sorghum, groundnuts, and cotton, across the three groups in the 2012 round. The three groups are conditionally comparable in the pre-treatment period. In assigning districts to traditional and multicrop FISP, the multicrop is defined for each crop. That is, a district is considered multicrop for sorghum if it received sorghum in addition to maize inputs, irrespective of the status of the other crops.

The table has the limitation of too few observations in some combinations of crop and FISP type. For instance, there were only twelve (12) sorghum fields in the e-voucher sub-sample and 98 cotton fields in the traditional FISP.

Table 3.6: Household-level yield of selected crops across groups in 2012

Crop	Traditional			Multicrop				E-voucher			
	obs	mean	sd	obs	mean	sd	diff[1]	obs	mean	sd	diff[2]
Maize	1,610	2,001	1,632	3,726	2,437	1,715	436***	1,093	2,303	1,724	302***
Sorghum	82	587	589	237	940	927	353***	9	536	285	-50.60
Groundnuts	766	652	604	2,489	540	545	-112***	665	471	486	-180***
Cotton	4	883	320	966	1086	806	203	260	781	535	-102

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

[1] difference in yield between multcrop and control districts.
[2] difference in yield between e-voucher and control districts.

The mean yield of maize in the pre-reform period is lowest in the traditional FISP districts, at $2001kg/ha$, and highest in the multicrop FISP districts at $2437kg/ha$. The statistical test also confirms that the level of yield is higher in the 'to-be-treated' districts than in the control. This reinforces the argument that selection to treatment was potentially influenced by each district's agricultural potential.

The yield of sorghum is highest in the multicrop districts, at about $940kg/ha$, significantly higher than yield in the control districts at $\alpha = 0.01$, but no statistical difference between the e-voucher and control districts. For instance, sorghum yield in e-voucher districts is about half the yield realised in multicrop districts. Sorghum is known to be suitable to low-lying, 'off the line of rail' regions of the low-rainfall agro-ecological zone (Jain, 2007). There were also more sorghum growers in multicrop districts than in the other groups of districts. The yield of groundnuts is highest in the traditional FISP districts, at $652kg/ha$, and lowest in the e-voucher districts at $471kg/ha$. The stastistcal tests show that the yield of groundnusts in the treated districts was lower than the yield in the control districts. The yield of cotton is highest in multicrop districts at $1086kg/ha$ and lowest in e-voucher districts, although the differences are not statistically significant. It is also worth noting that there are more crops grown in multicrop districts, partly because of having more districts in this category than in the others. Interestingly, there are very few cotton growers in traditional districts, and very few sorghum growers in e-voucher districts.

Since the assignment of districts into the treated and control groups was criteria-based, some of the differences in yield must be expected. Districts were chosen for their perceived suitability for the inputs provided.

3.5.1.4 Crop diversification

Crop diversification is an intermediate step towards the practice of crop rotation (Kassie et al., 2013; Liebman and Dyck, 1993). As discussed earlier in subsection 3.4.1.2, crop diversification is measured by the Simpson index of diversification (SID) on the basis of the area cultivated, as defined in eqn. 3.7. The index is zero for a monocropping farmer and close to one for a perfectly diversified farmer. A more practical definition has been put forward by Jones et al. (2014) that the index measures the probability that two randomly selected fields will have crops of different types. Descriptive results for the different groups for the two waves are shown in table 3.7.

Table 3.7: Simpson index of CD

Type of FISP	2012					2015				
	obs	mean	sd	min	max	obs	mean	sd	min	max
Traditional FISP	1,897	0.338	0.255	0	0.794	1,871	0.335	0.249	0	0.8
Multicrop FISP	4,125	0.461	0.238	0	0.855	4,103	0.444	0.225	0	0.84
E-voucher FISP	1,121	0.329	0.23	0	0.793	1,115	0.293	0.23	0	0.798
Total	7,143					7089				

The level of CD is around 0.34 and 0.45 in traditional and multicrop FISP districts respectively, with not much change between the two waves. The index is lowest in the e-voucher districts, at 0.33 in 2012 and 0.29 in 2015. The level of diversification of crops seems to be lower among farmers in e-voucher districts. As mentioned in subsection 3.5.1.2, farmers in e-voucher districts seem to make more private investment in farming, own more assets, and produce more crops. This may imply that they produce more cash crops, and commit large portions of their fields to one or two crops, leading to a lower level of diversification. The level of the index on the overall diversification is comparable to other studies, such as that of Kankwamba et al. (2018), who found an average SID of between 0.39 and 0.47 in Malawi, and Basavaraj et al. (2016) and Mithiya et al. (2018), who found a SID of around 0.7 in selected regions of India.

3.5.1.5 Adoption of crop rotation

In order to assess the adoption of crop rotation, each farmer was asked what crop was planted in the field in the year of data collection and the two preceding seasons. A field is said to have been crop-rotated if the crop in at least one season was different. This definition is in line with other studies in which crop rotation is defined on a three-season basis (Andersson and D'Souza, 2014; Arslan et al., 2015). For each farmer, the proportion of cultivated land on which crop rotation was practised is computed using eqn. 3.16. The descriptive results are shown in table 3.8.

Table 3.8: Intensity of crop rotation

Type of FISP	2012					2015				
	obs	mean	sd	min	max	obs	mean	sd	min	max
Traditional FISP	1,915	0.378	0.379	0	1	1,891	0.312	0.335	0	1
Multicrop FISP	4,134	0.593	0.365	0	1	4,120	0.511	0.376	0	1
E-voucher FISP	1,124	0.505	0.392	0	1	1,123	0.407	0.37	0	1
Total	7,173					7,134				

On average, farmers in traditional FISP districts rotated 37% of their cultivated hectarage, while those in multicrop FISP practised crop rotation on about 60% of their fields in the 2012 round. Farmers in e-voucher districts rotated crops on about half of their cultivated fields. Further examination reveals that the intensity of crop rotation is pulled down by high numbers of non-adopters.

There is also a noticeable decrease between 2012 and 2015. Dis-adoption of newly adopted farming technologies has been noted in a number of studies, often driven by the cessation of incentives that are usually provided under projects (Andersson and D'Souza, 2014; Arslan et al., 2014; Haggblade and Tembo, 2003). In some cases, dis-adoption or abandonment comes after the promotion of new farming practices without convincing evidence of their effectiveness or benefits (Habanyati et al., 2018; Jayne et al., 2018b; Pedzisa et al., 2015a; Wineman et al., 2020). The decrease in the proportion of land under crop rotation is highest among farmers in e-voucher districts where the average intensity dropped by about 9 percentage points.

3.5.1.6 Test for attrition bias

Attrition occurs when households that are observed in the first wave are not observed in the second or successive waves. Replacement is also not tenable if the benefits of the panel properties of the data are to be maintained. The two rounds of the RALS data have an attrition rate of about 18%. Similar studies such as Xu et al. (2009), have also observed an attrition rate of around 18%, while Asfaw and Davis (2018) observed an attrition rate of 8.7% over two years. There are many reasons why households may not be captured in subsequent rounds. In the RALS data, the major causes of attrition are households moving out of the SEA, which accounted for 60.1% of lost respondents. Others are the dissolution of households, accounting for 18.4%, and lost contact at 19.9%. Refusal was very low at 1.7%.

Attrition in panel data sets has the potential to bias the results if the factors driving attrition are also related to factors driving the variables of interest. The chapter performs a regression-based test for attrition bias in line with Xu et al. (2009). First, a binary indicator variable is defined to categorise respondents into those forming the panel and those lost. Then each dependent variable is regressed on the potential covariates and the binary attrition indicator, using the pre-treatment observations. Attrition is said to be a problem if the attrition indicator variable is shown to significantly affect outcome variables. The abridged regression results are presented in table 3.9 while the full results are presented in table C.1 in appendix C. Columns 1 and 2 have the regression on the yields of maize and groundnuts, respectively, and columns 3 and 4 have crop diversification and crop rotation, respectively.

Table 3.9: Auxiliary regression for test of attrition bias

	(1)	(2)	(3)	(4)
VARIABLES	Yield_maize	Yield_gnuts	SID	CR
attrition	1.401 (74.151)	12.218 (31.179)	0.002 (0.010)	-0.014 (0.017)
	⋮	⋮	⋮	⋮
Observations	4,436	2,857	4,178	4,178

SEA clustered robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results in table 3.9 consistently show an insignificant attrition indicator in all the four regressions. Although attrition may be said to be high at 18%, the results show that the dependent variables are independent of attrition. There is no difference in the dependent variables between respondents forming the panel and those who have been lost to attrition. The loss of 18% of the observations does not bias the results. The chapter therefore proceeds to work with the stated panel, without requiring any remedial measures.

The discussion above has highlighted some features of the sample and how the three groups compare. While there are no noticeable systematic differences in demographic characteristics, there are marked differences in the ownership of important farming assets, such as cattle and other implements, among the three groups. The acquisition and use of fertiliser also seem to be different, with e-voucher districts depending more on cash purchases while the others mainly depend on FISP. In addition, the average quantities of fertiliser used per household were higher in e-voucher districts. The three outcome variables also seem to be different among the three groups even in the pre-treatment period.

Although these differences are not statistically tested, they do provide a basis for the use of methods that control for systematic differences among treated and control groups, as suggested in this chapter. On the other hand, tests for attrition rule out the need for any corrective measures.

3.5.2 Results and Discussions

This section discusses the results and findings. Section 3.5.2.1 looks at the impact of FISP reforms on crop yield. Sections 3.5.2.2 and 3.5.2.3 look at the impact of the reforms on the degree of crop diversification (CD) and the intensity of crop rotation (CR), respectively.

3.5.2.1 The impact of FISP reforms on crop yield

The impact of FISP reforms on crop yield is estimated using the Cobb-Douglas formulation in eqn. 3.12. In this subsection, the regressions on yield are crop-specific, as discussed in section 3.5.1.3. The definition of treatment is also modified, using the e-voucher as the treatment and the traditional FISP as the control. The DiD estimation results are shown in table 3.10. Column (1) has the OLS, columns (2) and (3) have the IPWRA and ESR, respectively while column (4) presents the PSM results. In all the four columns, the dependent variable is yield, expressed in natural log.

Table 3.10: Treatment effect on maize yield

VARIABLES	(1) OLS	(2) IPWRA	(3) ESR	(4) PSM
Dependent variable[1]	ln(yield)	ln(yield)	ln(yield)	ln(yield)
treated_ev	-0.179*** (0.063)	-0.233** (0.107)	-0.529*** (0.101)	-0.265*** (0.079)
group_ev	-0.128** (0.057)	0.063 (0.100)	-0.056 (0.059)	
period	0.049 (0.048)	0.081 (0.082)	0.062 (0.046)	
fd	-0.578*** (0.057)	-0.769*** (0.164)	-0.573*** (0.055)	
education	0.015** (0.006)	-0.011 (0.013)	0.017*** (0.006)	
age	0.012* (0.007)	0.050*** (0.015)	0.012* (0.007)	
age2	-0.000* (0.000)	-0.000*** (0.000)	-0.000* (0.000)	
gender(male=1)	0.113 (0.078)	0.015 (0.108)	0.122 (0.076)	
adult_number	-0.009 (0.008)	-0.002 (0.013)	-0.003 (0.008)	
cattle_number	0.003*** (0.001)	0.005*** (0.002)	0.003*** (0.001)	
any_trained	0.022 (0.039)	0.006 (0.075)	0.034 (0.037)	
land_used	-0.038*** (0.006)	-0.035** (0.014)	-0.035*** (0.006)	
soc_net_coop	0.159** (0.063)	0.346*** (0.096)	0.180*** (0.068)	
R_minus	0.025* (0.015)	0.070** (0.028)	0.013 (0.013)	
Constant	7.698*** (0.190)	6.727*** (0.519)	7.674*** (0.186)	
Observations	2,164	1,635	2,164	911

SEA clustered robust standard errors in parentheses[2] *** p<0.01, ** p<0.05, * p<0.1

[1] ln(·) is the natural log.

[2] PSM use robust Abadie-Imbens standard errors (Abadie and Imbens, 2006).

The results show a highly significant negative impact of the e-voucher reform on the yield of maize. The results indicate that the introduction of the reform could be associated with a 20% fall in maize yield, although the ESR gives a much high estimate. These results are consistent with prior expectations that with the introduction of the e-vouchers, farmers have the liberty to apply resources that might have otherwise been used for maize inputs to other crops or ventures. This has the potential to reduce the quantity of resources (or fertiliser) applied to maize, and hence a possible reduction in maize yield. A number of studies (Jayne and Rashid, 2013; Liebman and Dyck, 1993; Tessema et al., 2015) have shown the importance of fertiliser use to crop yield. A reduction in fertiliser use can negatively impact yield.

To measure the impact of reforms on the yield of groundnuts, treatment is defined by receipt of FISP which includes inputs for groundnuts. The DiD estimation results are shown in table 3.11. Similarly to table 3.10, column (1) has the OLS, (2) and (3) IPWRA and ESR, respectively while (4) is the PSM. The dependent variable is the yield of groundnuts expressed in natural log.

Table 3.11: Treatment effect on groundnuts yield

VARIABLES	(1) OLS	(2) IPWRA	(3) ESR	(4) PSM
Dependent variable[1]	ln(yield)	ln(yield)	ln(yield)	ln(yield)
treated_gnuts	0.110 (0.072)	0.030 (0.079)	0.130 (0.083)	0.079 (0.089)
group_gnuts	-0.215*** (0.060)	-0.197*** (0.073)	-0.214*** (0.060)	
period	0.051 (0.068)	0.128* (0.069)	0.044 (0.069)	
fd	-0.108* (0.063)	-0.134* (0.075)	-0.110* (0.062)	
education	0.017** (0.007)	0.017** (0.008)	0.017** (0.007)	
age	0.004 (0.007)	-0.002 (0.009)	0.004 (0.007)	
age2	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	
gender(male=1)	-0.103 (0.089)	0.007 (0.095)	-0.104 (0.088)	
adult_number	-0.006 (0.010)	-0.006 (0.010)	-0.006 (0.010)	
cattle_number	0.007*** (0.002)	0.006*** (0.002)	0.007*** (0.002)	
any_trained	-0.044 (0.036)	-0.006 (0.046)	-0.043 (0.036)	
land_used	-0.025*** (0.009)	-0.028*** (0.011)	-0.025*** (0.009)	
soc_net_coop	0.022 (0.067)	0.022 (0.068)	0.021 (0.067)	
R_minus	-0.006 (0.013)	-0.009 (0.016)	-0.005 (0.013)	
Constant	6.334*** (0.213)	6.433*** (0.314)	6.331*** (0.212)	
Observations	2,752	2,734	2,752	912

SEA clustered robust standard errors in parentheses[2] *** p<0.01, ** p<0.05, * p<0.1

[1] ln(·) is the natural log.

[2] PSM use robust Abadie-Imbens standard errors (Abadie and Imbens, 2006).

The impact of reforms on the yield of groundnuts is slightly different. The estimated impact of providing groundnut inputs on groundnuts yield is generally insignificant, albeit leaning to the positive side. This might be explained by the low quantities of groundnut inputs provided. For instance, districts that were allocated groundnuts inputs received a combined total of 2,185 packs of groundnut inputs, compared to a combined total of 68,442 maize packs (MoA, 2013a). This translates to the number of groundnut packs being about 3% of the number of maize packs. Hence, far fewer farmers benefit than is implicitly assumed in the model. It is safe to conclude that the provision of inputs for other crops has not had an appreciable impact on the yield of the supported crops. Perhaps as the quantity of those inputs improve, a significant impact might be seen. With the entrenched culture of monocropping and the heightened emphasis on maize (Andersson and D'Souza, 2014; Habanyati et al., 2018; Maggio et al., 2018), there is also a possibility of farmers re-allocating the additional fertiliser to maize.

Even though the table has controlled for a number of variables, there are still visible differences in yield between the treated and control groups. In particular, the yield in the treated was about 20% lower than yield in the control group.

The coefficients on FD in the maize yield (table 3.10) are significantly negative but insignificant in groundnuts regressions (table 3.11). Farmers who are highly dependent on FISP tend to have lower maize yields. A farmer fully dependent on FISP will have a maize yield lower by around 60% compared to a comparable farmer who does not depend on FISP at all. This is not strange, given that dependence is associated with economic status as well as access to inputs. Economically disadvantaged farmers will not only lack fertiliser and seed, but other implements which are important for production. There might also be a tendency among economically constrained households to spread the fertiliser thinly over large areas of crop.

The level of education in a household and the number of cattle owned also influence crop yield. The results show that education in a household has a significant effect on yield. This is consistent for both maize and groundnuts and can be extended to agricultural productivity in general. An additional year of education has potential to raise yield by about 2%. While other studies, such as Pedzisa et al. (2015b), did not find a significant impact of education on yield, the results here show a strong impact. A positive impact of education on yield could potentially arise from the broader definition of education applied in this thesis, which takes into account the educational level of other members in a household.

The coefficient on the number of cattle owned is significant in both the maize and groundnuts yield estimations. This suggest that households that own more cattle tend to have higher yields than comparable households with fewer or no cattle. For instance, every additional pair of cattle is associated with a percentage increase in yield, reflected in both maize and groundnuts estimates. On the other hand, the area of land being cultivated is negatively associated with yield. With more land to work, there could be a tendency for farmers to spread available resources, such as manpower and fertiliser, thinly over more of their land. Households with small areas of land can afford to concentrate their management skills and resources, which has a net benefit on yield.

Membership in farmer cooperatives is strongly significant on maize yield but insignificant on groundnuts. As was alluded to earlier in subsection 3.5.1.1, membership is a prerequisite for the receipt of FISP inputs and other extension services. Therefore, farmers holding such memberships are more likely to receive or to benefit from subsidies and to receive the information necessary for agricultural productivity. As mentioned already, the production of maize is more dependent on subsidies than groundnuts and many other crops, hence the observed differences in the effect.

The amount of seasonal rainfall has a positive impact on the yield of maize but a completely insignificant one on the yield of groundnuts. This may indicate different levels of dependence on rainfall or resilience to rainfall shocks for different crops, an important aspect of the move to crop diversification (Lin, 2011; Mulwa et al., 2017). These results show that maize yields will fluctuate with rainfall performance more than groundnuts yields. Other variables such as age, household size, and training do not seem to be important for crop yield.

3.5.2.2 The impact of FISP reforms on the degree of crop diversification

The estimation of the impact of FISP reforms on CD is based on eqn. 3.13. The DiD estimation results are presented in table 3.12. Column (1) has the OLS. Columns (2) and (3) have the IPWRA and METEM, respectively while columns (4) and (5) are PSM results for the multicrop and e-voucher treatments, respectively. The PSM estimation is performed separately on re-defined binary treatment variables[9] as the PSM does not permit multi-valued treatments.

Table 3.12: Impact of FISP reforms on crop diversification

VARIABLES	(1)	(2)	(3)	(4)	(5)
	OLS	IPWRA	METEM	PSM[2]	PSM[2]
Dep. variable[1]	SID	SID	SID	SID	SID
treated_mk	0.070*** (0.013)	0.079*** (0.015)	0.161*** (0.040)	0.095*** (0.017)	
treated_ev	-0.095*** (0.020)	-0.072*** (0.024)	-0.031 (0.037)		-0.035 (0.028)
period	-0.022 (0.014)	-0.009 (0.016)	-0.020 (0.017)		
group	0.009 (0.007)	-0.015 (0.010)	0.008 (0.013)		
fd	0.122*** (0.011)	0.121*** (0.016)	0.121*** (0.014)		
education	-0.009*** (0.001)	-0.009*** (0.002)	-0.009*** (0.001)		
age	0.006*** (0.001)	0.008*** (0.002)	0.006*** (0.002)		
age2	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)		
gender	-0.001 (0.015)	-0.016 (0.024)	-0.000 (0.016)		
adult_number	-0.003* (0.002)	-0.005** (0.002)	-0.006*** (0.002)		
cattle_number	-0.002*** (0.000)	-0.001*** (0.000)	-0.002*** (0.000)		
trained	0.022*** (0.007)	0.044*** (0.011)	0.026*** (0.009)		
land_used	0.010*** (0.002)	0.011*** (0.002)	0.009*** (0.002)		
_Ifarm_cate_B	0.075*** (0.007)	0.086*** (0.011)	0.075*** (0.009)		
_Ifarm_cate_C	0.049*** (0.009)	0.072*** (0.013)	0.050*** (0.012)		
member_coop	0.006 (0.011)	-0.012 (0.020)	0.006 (0.012)		
R_minus	0.020*** (0.002)	0.020*** (0.003)	0.020*** (0.003)		
R_minus_1	-0.024*** (0.002)	-0.017*** (0.004)	-0.024*** (0.005)		
Constant	0.193*** (0.041)	0.107* (0.059)	0.176*** (0.055)		
Observations	5,910	5,910	5,910	2,493	1,153

SEA clustered robust stand ard errors in parentheses[3] *** p<0.01, ** p<0.05, * p<0.1

[1] SID is Simpson (1949) index of diversification. *See* eqn. 3.7.

[2] The PSM estimates are based on binary treatment variables (multicrop vs traditional, and e-voucher vs traditional)

[3] PSM use robust Abadie-Imbens standard errors (Abadie and Imbens, 2006).

The results in table 3.12 show varying impacts of the two FISP reforms. The results show a positive impact on the level of CD of the introduction of multiple crops (*treated_mk*). The coefficient on multicrop reform is positive and statistically significant across the four estimators. Multicrop treatment increases the level of CD by between 6 and 12 percentage points. These results are consistent with expectations and suggest that the additional inputs do not completely crowd out private investment in other crops. Farmers who benefit from inputs of 'other' crops end up growing more of the 'other' crops, leading to increased level of crop diversification at the household level. This was also observed by Jayne et al. (2018b) at a continental level and Koppmair et al. (2017) in Malawi.

The e-voucher programme (*treated_ev*), on the other hand, is only significant in the OLS

[9] The binary treatment variables are defined for each treatment. Multicrop has 1 for households in multicrop districts, 0 for households in the traditional FISP and missing for households in the e-voucher districts and similarly for e-voucher treatment.

and IPWRA, but insignificant under the METEM and PSM, albeit leaning on the negative. This chapter hypothesised that the introduction of the two reforms would foster CD and this was supported by the programme's objective of promoting CD (MoA, 2013b). The e-voucher programme also gives more flexibility to the farmers, and therefore was expected to have a positive impact on CD. However, the results here are inconclusive, but point to a possible negative impact. These results are also supported by a number of key informants who argue that the e-voucher did not cause any switching to other crops as was envisaged in the policy. The following excerpts provide some intuitive responses on why the e-voucher programme produces results that do not conform to expectations.

> *''The e-voucher is open, the farmer can get even soybeans, groundnuts. Somehow, it has helped for farmers who have interest in CD. They are able to get the crops they want. It is not restricted although farmers still have that belief of maize and fertiliser. There is little increase in the hectare of other crops since the e-voucher but the increase has not been much. There is so much concentration on maize, maybe [because] it is our staple crop and others it is because that is what parents were growing.'' (CH,M)*
>
> *''That's the essence of e-voucher system. But the attitude of the farmers, mostly they redeem inputs like fertiliser and maize. Only a few are doing that [CD]. We are preaching to them to diversify.'' (CH,F)*
>
> *''Even after the introduction of the e-voucher system, monoculture still remains high. Even when you go into town, you would find that all agro-shops have maize and fertiliser only. Because if you look at the e-voucher, farmers are able to redeem what they want. For example, they can get wire fencing, they can get drugs, they can get anything related to agriculture. But it is like our farmers here, maize, that is what is in them. Some time back they could say that this project we want fencing. Because for those who have problems with garden fencing, they would have done that using the e-vouchers. But still, even if you go there today, in these agro-shops, you would find that it is fertiliser and maize.'' (MO,F)*
>
> *''But this current season, I don't know what has happened maybe because of the pressures we have from the last season, issues of food security, we saw a lot of farmers still going back to maize and fertiliser. Of course you can't really blame them, the issues of market. Farmers [here] can grow anything as long as they have an assured market. Because of issues of markets, you find them involuntarily going back to maize production.'' (MO,F)*

A number of challenges inhibiting the adoption of CD have been highlighted. For instance, while the e-voucher provides flexibility in the inputs a farmer can get, there are still rigidities in the supply of inputs for other crops by the private sector. The private sector has not yet moved to providing inputs for other crops in commensurate quantities. There are still observable stock-outs of inputs for other crops that farmers may want to acquire. This is believed to have the impact of reinforcing the cultivation of maize, for which the supply of inputs is well established. These inefficiencies were also noted by Jayne et al. (2018b) as having the potential to weaken the impact of subsidy programmes. This also explains why a multicrop FISP is successful in promoting CD while the e-voucher system, which leaves the choice to the farmers, fails to increase CD.

The statements from key informants also show that while access to necessary inputs was one hindrance to CD, there are other barriers as well. Farming is a business and the importance of having markets for various crops should not be underestimated. While the country's food reserve programme has provided a reliable market for maize, there are still challenges in accessing markets for other crops. There is also an inherent culture of cultivating traditional crops, mainly maize.

The FD is highly significant, suggesting that farmers who are highly dependent on FISP tend to have high levels of diversification. Because they depend on FISP for inputs, these farmers are likely to grow limited quantities of many crops. On the other hand, farmers less dependent on FISP are normally economically advantaged and more likely to grow large quantities of a few crops or tend to concentrate on cash crops. This would have the effect of lowering the level of CD, as observed here.

The coefficient on education is significantly negative, suggesting that a higher level of education in a household is associated with a reduced level of CD. Age has a positive influence on the level of CD, but beyond a certain age, estimated at around 40 years, farmers tend to concentrate on fewer crops. Age is associated with the accumulation of knowledge, experience, and physical and social capital (Kassie et al., 2013). This would lead to an increasing level of CD. However, beyond a certain level, age is associated with lost energy and a shorter planning horizon (Kassie et al., 2013, 2015a; Pedzisa et al., 2015b), which might contribute to concentration on 'basic' crops. There are no differences between female and male dominated households in the level of CD.

Households owning more cattle tend to have low levels of CD. With more physical capital and draught power at their disposal, this category of farmers is more likely to concentrate on cash crops. However, when large areas of land are available, there is a high level of CD. The same is true for category B and C farmers, who cultivate more land than category A farmers. This may suggest that lack of sufficient land could be hindering the progress of CD among smallholder farmers.

Similarly, receipt of training is also associated with an increased level of CD. Training of farmers takes different forms and is offered by both the government through AEOs and by cooperating partners. Training includes orienting farmers on rainfall variability and on adaptation strategies, which is why training leads to increased levels of CD. There are also indications that membership in farmers' groups such as women's groups and local saving and loans societies is associated with higher levels of CD. Farmers' groups provide a platform for farmers to share information, and to receive extension services and FISP inputs. Therefore, farmers who belong to these groups are expected to have more knowledge and appreciation of the importance of CD.

Crop diversification is required so as to prepare for periods of erratic or low rainfall. The results show a positive contemporaneous effect but a negative lagged effect, suggesting that farmers respond to poor rainfall by diversifying the crop base but will respond differently from past experience of poor rainfall. In particular, poor rainfall in the preceding season is associated with reduced CD. This could be due to the conflicting effect of poor rainfall on decision making regarding CD. Farmers may want to diversify in response to anticipated poor rainfall, but the poor rainfall my not give enough time to venture into other crops. There is also a tendency among smallholder to prioritize maize, before planting other crops (Maggio et al., 2018). This is supported by a key informant who stated that:

> *''Our farmers have not grown a lot of crops right now, they still wanted to plant but the rains are gone. They just concentrated on maize immediately they received early rains. Most of them planted maize than other crops. Other crops, that is when they wanted to start.'' (MO,F)*

When rainfall is poor, farmers may desire to spread the downside risk by growing more alternative crops, enhancing the level of CD. At the same time, the poor rainfall implies that there is little opportunity to venture into multiple crops. Instead, farmers may concentrate on the staple crop.

3.5.2.3 The impact of FISP reforms on adoption of crop rotation

The impact of FISP reforms on the adoption of crop-rotation practices is hypothesised to pass through CD, as well as other channels. FISP reforms allow farmers to diversify their crop bases by easing access to the inputs of other crops. This section estimates the impact of reforms on the proportion of land under crop rotation using the METEM model in eqn. 3.14. The DiD regression results for the impact of FISP reforms on the intensity of CR are presented in table 3.13. Column (1) is the OLS, (2) is the IPWRA and (3) is the METEM. Columns (4) and (5) are PSM results for the multicrop and e-voucher treatments, respectively, estimated using redefined binary treatment variables.[10]

The results show a statistically significant positive impact of multicrop reform (*treated_mk*) on the intensity of crop rotation at a household level. The coefficient is significant across the four estimation methods. Under the assumption of *ceteris paribus*, the multicrop reform raises the intensity of CR by more than 15 percentage points. This means that the FISP reform of providing inputs for multiple crops is effective in promoting the intensification of crop rotation among recipient farmers.

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[10] A binary treatment variable is defined for multicrop treatment and another for e-voucher treatment. *See* note 9 on page 102.

Table 3.13: Impact of FISP reforms on proportion of land under crop rotation

VARIABLES	(1) OLS	(2) IPWRA	(3) METEM	(4) PSM	(5) PSM
Dependent variable[1]	p_CR	p_CR	p_CR	p_CR	p_CR
treated_mk	0.111*** (0.019)	0.136*** (0.022)	-0.002 (0.085)	0.190*** (0.026)	
treated_ev	0.086*** (0.030)	0.093*** (0.036)	0.317*** (0.076)		0.157*** (0.054)
period	-0.161*** (0.021)	-0.133*** (0.024)	-0.167*** (0.026)		
group	0.018 (0.012)	0.017 (0.014)	0.022 (0.018)		
SID	0.538*** (0.022)	0.577*** (0.030)	0.541*** (0.027)		
fd	-0.066*** (0.017)	-0.041 (0.025)	-0.062*** (0.020)		
education	-0.006*** (0.002)	-0.008*** (0.003)	-0.005*** (0.002)		
age	-0.008*** (0.002)	-0.008** (0.003)	-0.007*** (0.002)		
age2	0.000*** (0.000)	0.000* (0.000)	0.000** (0.000)		
gender	0.002 (0.025)	-0.040 (0.035)	0.001 (0.024)		
adults (number)	0.002 (0.003)	0.003 (0.003)	0.001 (0.005)		
cattle (number)	-0.000 (0.000)	0.000 (0.001)	-0.001** (0.000)		
trained	0.058*** (0.011)	0.051*** (0.016)	0.041*** (0.015)		
land_used	-0.001 (0.002)	-0.003 (0.003)	-0.000 (0.002)		
_Ifarm_cate_B	0.004 (0.012)	-0.007 (0.017)	0.006 (0.011)		
_Ifarm_cate_C	0.011 (0.014)	0.020 (0.019)	0.012 (0.015)		
member_coop.	0.004 (0.017)	-0.021 (0.028)	0.006 (0.017)		
R_minus	-0.013*** (0.003)	-0.003 (0.004)	-0.011** (0.005)		
R_minus_1	0.017*** (0.004)	0.018*** (0.005)	0.016** (0.006)		
Constant	0.548*** (0.065)	0.546*** (0.095)	0.548*** (0.070)		
Observations	5,910	5,910	5,910	2501	1157

SEA clustered robust standard errors in parentheses[2] *** p<0.01, ** p<0.05, * p<0.1

[1] p_CR is the proportion of land under crop rotation. *See* eqn. 3.16.
[2] PSM use robust Abadie-Imbens standard errors (Abadie and Imbens, 2006).

On the e-voucher reform (*treated_ev*), the coefficient is largely insignificant, albeit positive, suggesting that the e-voucher reform has had a limited impact. It was shown earlier, in subsection 3.2.4, that the FISP reforms have two pathways to intensity of crop rotation. In figure 3.1, there is a direct impact, captured as the treatment effect here, and an indirect impact through its effect on the level of CD. The preceding subsection showed that the multicrop reform had a positive impact on CD, while the impact of the e-voucher reform on CD was insignificant. This could explain the weak results observed here for the impact of the e-voucher reform on the intensity of crop rotation. These results are comparable to other studies. For instance, Jayne et al. (2018b) concluded that input subsidy programmes have the potential to influence farmers' behaviour towards the adoption of CSA practices such as CD and CR while Koppmair et al. (2017) found a positive association between participation in input support programmes and the adoption of legume intercropping.

The coefficients on FD are insignificant. The intensity of crop rotation among farmers is not affected by the level of dependence on FISP. The degree of CD performs strongly as a driver of the intensity of crop rotation at the household level. The coefficients are consistently significant. A change from monocropping to perfectly diversified farming would increase the intensity of crop rotation by more than 50 percentage points, *ceteris paribus*. Further examination shows that the coefficient on SID increases from traditional FISP, to multicrop FISP, and ultimately in the e-voucher districts. Crop diversification seems to enhance crop rotation more in e-voucher districts than in multicrop districts, and similarly, more beneficial to crop rotation in multicrop districts than in traditional FISP districts. This suggests that access to inputs of other crops and the level of CD complement each other in the adoption of crop rotation. These results are also supported by qualitative findings, as demonstrated in the following excerpts.

> *"Usually, legumes they plant small areas compared to cereal crops. So now to rotate cereal crop where a legume was, it can't fit properly." (CH,M)*
> *"You find that the maize portion is very big and for groundnuts very small. So next year, you find it will not balance, ... They don't have equal portions of land to balance with maize. Farmers are concentrating much on maize" (CH,M)*
> *"Then crop rotation also, monoculture is also high ... because the farmers would say, this is the only field I rely on where I harvest maize. So why should I plant a legume?" (MO,F)*
> *"Most of the farmers [here] are maize growers, they don't rotate their fields but we have explained to them the importance of crop rotation" (MO,F)*

The above statements would lead one to conclude that the adoption or practice of crop rotation among smallholder farmers is hampered by the low levels of CD. A detailed discussion of the drivers of CD was presented in the preceding section, and it is clear that the issues of markets and access to the inputs of other crops remain the major barriers.

The intensity of crop rotation declines with the age of the household head and the level of education in the household. Age is associated with loss of energy and a shortening planning horizon (Kassie et al., 2013, 2015a; Pedzisa et al., 2015b). At the same time, age also brings a specialisation in cash and staple crops, which would have the effect of inhibiting the practice of crop rotation, as such farmers tend to cultivate areas of staple/cash crops that are too large for meaningful rotation with legumes. The level of education in a household is hypothesised to improve knowledge and the appreciation of new farming practices. At the same time, and as noted by Kassie et al. (2013) and Zulu-Mbata et al. (2016), education may also be positively related with access to non-farm incomes. This may lead to reduced attention to farm activities and concentration of few crops.

Farmer training and extension services remain important for promoting the adoption of new farming technologies. The results here show that farmers who reported receiving any CR-related training tended to have a higher intensity of CR. As expected, education or training helps farmers to appreciate the importance of crop rotation and promotes its adoption. These results conform to findings from a number of studies, both in Zambia and elsewhere (Abdulai, 2016; Habanyati et al., 2018; Kassie et al., 2013; Mulwa et al., 2017).

Other important variables include the measures of remoteness, which include the distances to a tarred road, a network coverage, and an agro-dealer. The results show that farmers who are remote tend to practice lower levels of crop rotation. This is consistent with findings from other studies, such as Arslan et al. (2014) and Feliciano (2019), which found a negative association between distance to a tarred road and adoption of new farming technologies. Very remote farmers are deprived of access to information and to appropriate tools and implements that would support the intensification of crop rotation. Access to markets for other crops also remains a challenge for these farmers, who therefore rely on the FRA mainly for the staple crop.

Rainfall may have two opposing effects on the adoption of climate-related farming practices, such as CF in general and CD and CR in particular. In the first place, poor or low rainfall causes farmers to diversify the crop base in order to spread their risk and, in the process, they practice crop rotation. This will produce a negative coefficient. At the same time, poor or low rainfall does not give farmers enough time to cultivate other crops, increasing their concentration on staple crops. This has the effect of stifling the practice of crop rotation and would produce a positive coefficient.

The results are generally insignificant on the contemporaneous effect but seemingly positive on the lag of rainfall shock, which measures the extent to which rainfall was low over the rainfall months (see eqn. 3.18). This implies that farmers respond to previous episodes of low rainfall by adopting crop rotation. Low rainfall in past farming seasons provides a push for the adoption of climate-smart agricultural practices. At the same time, low rainfall contemporaneously may limit the farmers' discretion on the adoption of these farming practices. Farmers exposed to low rainfall are likely to adopt climate-smart farming practices only in future farming seasons.

3.6 Conclusion

The chapter looked at the impact of FISP reforms on crop yields and the adoption of crop diversification and rotation practices, using a mixed-methods approach. In particular, econometric and qualitative methods were employed to answer questions about the impact of the introduction of multiple crops and of the e-voucher FISP on crop yield, degree of crop diversification, and the intensity of crop rotation among smallholder farmers. The chapter employed a combination of data sets comprising a two-wave panel from the RALS, high resolution satellite rainfall data, and administrative data on the distribution of FISP inputs. These were also supplemented with a primary qualitative survey of Agricultural Extension Officers. It used the DiD in combination with IPWRA, ESR and PSM to estimate the impact of FISP reforms on the selected outcome variables.

FISP reforms have been successful in altering the agricultural landscape among smallholder farmers. The reforms have allowed the cultivation of other crops as well as offering flexibility to farmers to respond to rainfall variations both over time and across space. The results show that the introduction of the e-voucher programme may have caused a decline in the yield of maize in the e-voucher pilot districts. The e-voucher programme allows farmers to apply subsidised inputs that could have been used on maize, such as improved seed and fertiliser, on other agricultural enterprises. This has been associated with a negative effect on the yield of maize, as established in the analysis. Similarly, the introduction of inputs for other crops on the FISP, such as groundnuts, is expected to help improve yields of the supported crops. However, there is not sufficient evidence that the supply of groundnut inputs helped increase the yield of groundnuts. The chapter has attributed the 'no impact' partly to the small proportion of inputs for other crops provided in the multicrop reform and the possibility to re-allocate the additional fertiliser to maize.

The results on the impact of the reforms on CD are mixed. The multicrop reforms is found to have a significantly positive impact on the level of CD. These results support the expansion of the multicrop FISP in order to promote CD, which is necessary for climate adaptation. However, the impact of the e-voucher reform is insignificant. While the e-voucher programme was designed to give farmers flexibility on what crops they grow, evidence shows that it did not caused a shift from maize to other crops, mainly for two reasons. First, there seems to be inertia because of an entrenched culture of producing maize. Secondly, the reforms were not complemented by an improved market supply of inputs and an assurance of output markets for alternative crops. The impact of reforms on the intensification of the practice of crop rotation is positive but is potentially underestimated by the indirect effect through CD. Our model has controlled for CD, allowing the estimation of the direct impact of reforms on crop rotation. Both reforms have significant positive impacts, although the multicrop has a larger coefficient.

However, the effectiveness of these reforms is hampered by a number of other factors. These include the absence of well-functioning markets led by the private sector for the inputs and outputs of alternative crops. Key-informant evidence suggests that farmers fail to respond to the stimuli of FISP reforms because they cannot find certified seeds of other crops on the market and because the output market is not as assured as is the case with maize which enjoys intervention buying by the Food Reserve Agency (FRA). In addition, farmers respond to early dry spells not by diversifying their crop base, but by concentrating on maize production on the *safety first* principle. Key-informant evidence also suggests that the culture of monocropping of maize is well entrenched among smallholder farmers. In the absence of a well-functioning crop insurance scheme and other social safety nets, the farmers' primary concern is securing the staple crop.

Promoting the adoption of climate-smart agricultural technologies among smallholder farmers through FISP reforms will require parallel reforms in other aspects of agriculture. In particular, there is a need for enhanced extension services and an improvement in markets for both inputs and outputs of alternative crops. There is also a need to promote small-scale mechanisation that would help mitigate the loss of animal draught power.

CHAPTER 4

DOES CONSERVATION FARMING IMPROVE CLIMATE RESILIENCE? THE CASE OF SMALLHOLDER FARMERS IN ZAMBIA

Chapter Abstract

This chapter employs the multinomial endogenous treatment effects approach to investigate the effectiveness of the adoption of conservation farming on mitigating the negative impacts of climate hazards on crop yields and resilience to climate change. The chapter combines a two-wave nationally representative rural agriculture livelihood survey (RALS) data and a high resolution satellite rainfall data, which allows the measurement of the impact of conservation farming at crop-plot level. From the satellite rainfall data, the chapter obtains a measure of precipitation extreme at household level, using an objectively measured rainfall performance.

The chapter finds that the adoption of conservation farming has a positive impact on crop yield, hence contributing to increased yield especially in periods of precipitation deficits. However, when there is sufficient rainfall, the adoption of conservation farming may actually be detrimental to crop yield. In addition, the results show that the adoption of conservation farming is also helpful in preventing weather induced crop failure. The chapter finds significant evidence that crops cultivated using conservation farming are more resilient to weather fluctuation, and able to survive harsh weather conditions compared to crops cultivated using conventional methods.

4.1 Introduction

The agricultural sectors of many developing countries continue to provide livelihoods to a large portion of the population. However, productivity remains low and is weather-dependent. The continued dependence on rainwater has exposed the agricultural sector, especially smallholder farmers, to severe effects of climate change, such as precipitation extremes (Lal et al., 2001). As argued already, the rainfall in Zambia has not only reduced in quantity, but have also become more erratic. This has contributed to food insecurity in affected regions (Jain, 2007), threatening the livelihood of the mostly rural households and hampering the attainment of the sustainable development goals of no poverty (SDG 1) and zero hunger (SDG 2).

Close to 57% of Zambia's households are rural, of which about 90% are classified as agricultural households (CSO, 2016a), and these often rely on rain-fed agriculture. The now erratic and reduced rainfall has had negative effects on crop performance for many smallholder farmers, resulting in situations of severe hunger. In order to mitigate the impact of erratic and reduced rainfall, government and cooperating partners have been promoting the adoption of climate-resilient agricultural practices. The main practice being promoted in Zambia is conservation farming (CFU, 2007, 2012; Kuntashula et al., 2014; Ngombe et al., 2014).

Conservation farming (CF) is a farming system that aims to improve soil and crop productivity and to stabilise yields under different agro-ecological conditions (Kuntashula et al., 2014; Mupangwa et al., 2016). It offers, among other things, an agricultural practice founded on efficient water use, and therefore one that minimises the negative effects of precipitation extremes on farm output.

From a theoretical standpoint, the benefits of conservation farming are twofold. Firstly, the emphasis on water-efficient agriculture helps improve resilience to rainfall variability (Busari et al., 2015; CFU, 2012; Hobbs, 2007; Montt and Luu, 2018), allowing crops to survive precipitation extremes such as dry spells or droughts. Secondly, conservation farming offers a sustainable way of using farming natural resources at a lower cost for sustained improvement in yields and food security (Arslan et al., 2014; Haggblade and Tembo, 2003; Hobbs, 2007). Despite these perceived benefits, the adoption rates remain low, while some farmers even dis-adopt the technology (Habanyati et al., 2018; Pedzisa et al., 2015a). The low levels of adoption may be partly due to farmers' uncertainty about the benefits and costs of conservation farming. Indeed, the impact of the adoption of conservation farming on output and resilience to rainfall variability has not been conclusively evaluated and shown to be of benefit in the Zambian context. There is no locally generated evidence showing that conservation farming actually improves yields or resilience in a typical smallholder farming scenario, a finding that could help authorities to speed up adoption (Andersson and D'Souza, 2014; Wall, 2007).

Studies from other countries cannot be relied upon in crafting specific action points, as the effectiveness of conservation farming may be influenced by the prevailing local climate, soil type, and farming system, which are region-specific and could vary even within a country (Hobbs et al., 2008; Naab et al., 2017). For instance, Zambia is divided into three agro-ecological zones (AEZ) which, as was shown in subsection 1.2.2, differ in major climatic variables. It remains unclear whether conservation farming would be suitable across all the agro-ecological zones of Zambia (Arslan et al., 2014).

Farmers will adopt conservation farming if they believe that it improves yields or mitigates against climate extremes. This chapter therefore seeks to examine the adoption of conservation farming (CF) and its impact on improving crop yield and minimising weather-induced yield fluctuations. This chapter attempts to provide answers to the following research questions:

- Does the adoption of CF increase crop yields among smallholder farmers?
- Does the adoption of CF reduce the negative impact of precipitation extremes on crops?

4.1.1 Objectives

The overall objective of this chapter is to examine the impact of the adoption of conservation farming on smallholder farmers' performance in the context of rainfall variability. The chapter is guided by the following specific objectives:

- to determine the impact of CF on crop yield.
- to determine the impact of CF in reducing crop failure induced by extreme weather.

4.1.2 Relevance of the Chapter

The findings in this chapter will inform policy on the effectiveness of CF in mitigating the impact of rainfall variability among rain-dependent smallholder farmers. The findings, if positive, will also give impetus to the adoption of CF among smallholder farmers and help reduce their vulnerability to rainfall variability.

The chapter will also contribute to the literature in a number of ways. Firstly, the chapter employs methods that are able to account for the endogenous choice to adopt CF practices on different crop plots (assignment to treatment). The literature on the impacts of the adoption of farming practices is dominated by methods that ignore the potential endogeneity in the assignment to treatment (Asfaw et al., 2017; Kuntashula et al., 2014; Mango et al., 2017; Michler et al., 2019). This chapter employs the multinomial endogenous treatment effects model (METEM) to estimate the impact of CF adoption on yield and climate resilience. The METEM allows for a multi-valued treatment and is able to control for the possible endogenous assignment of fields to treatment.

Secondly, the chapter employs a rich combination of data sets, something that is uncommon in the related literature (Hobbs et al., 2008; Michler et al., 2019; Montt and Luu, 2018; Naab et al., 2017; Tessema et al., 2015). The chapter is based on a two-wave nationally representative survey of rural (farming) households, combined with high-resolution satellite rainfall data. The use of large-scale household surveys to evaluate the impact of CF adoption in different contexts is recognised in the literature (Lalani et al., 2017). Although the benefits of CF adoption could be evaluated using on-farm/on-station experiments, these approaches have been criticised for their failure to reflect the reality of diverse farmers' situations appropriately (Soane et al., 2012). Farmers in such experiments often receive extensive training and both technical and material support on CF, and pest and disease control (Mupangwa et al., 2016), more than would normally be available outside the experiment. This chapter therefore uses a dataset which the literature recognises as more appropriate in this context.

Thirdly, the chapter measures the contribution of rainfall or weather extremes to the effectiveness of conservation farming. Although rainfall is a recognised contributor to crop performance in rain-fed agriculture, a meta-analysis by Brouder and Gomez-Macpherson (2014) shows that studies looking at the impact of the adoption of conservation farming on smallholder agricultural yields often fail to incorporate a measure of rainfall performance. In this chapter, each crop field/plot observation was linked to an objective measure of rainfall performance indicator. In an appropriate model, this captures the effectiveness of CF in attenuating the negative impact of rainfall extremity, such as excess rains or dry spells on crop performance. This approach is relatively new and this chapter will be informative on the suitability of such an approach.

The rest of the chapter is organised as follows. Section 4.2 provides the background while section 4.3 reviews the relevant literature. Section 4.4 presents the methodology for the chapter. Section 4.5 analyses the data and discusses the results and section 4.6 presents the conclusions that are drawn from them.

4.2 Background

This section provides a brief background of conservation farming, defining the concept (subsection 4.2.1) and how it impacts crop yield and climate resilience (subsection 4.2.2).

4.2.1 What is Conservation Farming?

The Food and Agriculture Organisation (FAO) defines conservation agriculture/farming as a farming system comprised of three principles: (1) minimum mechanical soil disturbance through the use of minimal or zero tillage methods, (2) permanent soil organic cover with crop residues and/or cover crops, and (3) the practice of diversified crop rotation, especially with legumes. CF is said to be beneficial in many aspects. These benefits can be categorised and more conveniently discussed under each principle of CF.

The principle of minimum tillage or soil disturbance is beneficial from both a cost and a conservation perspective. Minimum tillage has been found to cost less, both in terms of energy and time (Grabowski et al., 2014; Hobbs, 2007; Pittelkow et al., 2015). This makes minimum tillage attractive to farmers who have limited draught power. Many smallholder farmers in Zambia are now faced with limited draught power, especially after many episodes of livestock diseases in the country (Andersson and D'Souza, 2014; Baudron et al., 2007; Pedzisa et al., 2015b). Minimum tillage also helps to dampen peaked labour demand during land-preparation stages, allowing households to manage with limited household labour. Peaked labour demand during land preparation has been shown to contribute to delayed planting (Montt and Luu, 2018), which negatively affects crop performance. At the same time, minimum tillage also contributes greatly to soil conservation. It helps to reduce soil erosion, which is exacerbated by conventional, thorough tillage, which loosens soil, making it susceptible to wind and water erosion (Montt and Luu, 2018). Minimum tillage is also known to help minimise the exposure of moist soil, minimising evaporation, and hence improving the efficiency of water capture and use (Busari et al., 2015; Corbeels et al., 2014).

Permanent organic soil cover or mulching is important for protecting the soil from the eroding effects of wind and of water run-off. It also helps to activate and recycle nutrients and provide additional organic matter to improve soil structure. In times of low precipitation, soil cover has been shown to enhance water infiltration and conservation (Zheng et al., 2014). Many researchers have acknowledged the role of soil cover in enhancing water infiltration and better protection of the soil surface, both from winds and the scorching sun (Hobbs, 2007; Mango et al., 2017; Montt and Luu, 2018). This is important for minimising soil erosion, as well as water evaporation, improving the efficient use of the limited water resources.

The benefits of a diversified crop rotation include the efficient use of soil nutrients. This is made possible because crops root at different depths, therefore reaching nutrient deposits at different depths (Florentin et al., 2010; Tilman et al., 2002). In addition, crop rotation with legumes allows the farmer to benefit from the nitrogen-fixing characteristics of legumes (Corbeels et al., 2014; Koppmair et al., 2017). Crop rotation also helps to break the life cycles of crop-specific pests and diseases (Corbeels et al., 2014; Florentin et al., 2010; Koppmair et al., 2017; Tilman et al., 2002). In general, CF adoption is hypothesised to increase crop yield as well as to attenuate the negative impact of extreme weather on crop performance. In the long run, CF adoption also helps to conserve the soil, a vital agricultural natural resource.

The Zambian version of conservation agriculture includes a fourth principle of establishment of agro-forestry, using the apple-ring acacia (*faidherbia albida*)[1] (CFU, 2007, 2012). A farming system in the absence of agro-forestry is referred to as Conservation Farming (CF) (Arslan et al., 2014), and this study will use that term throughout.

While CF may seem to emphasise sustainability, its efficient use of water has become attractive for climate adaptation efforts. Its use as a strategy for adapting to rainfall variability is being promoted in order to build resilience to rainfall variability among smallholder farmers, whose agricultural success is dependent on good rains (Andersson and D'Souza, 2014; Arslan et al., 2015; Kassam et al., 2019; Zulu-Mbata et al., 2016). The Conservation Farming Unit has noted

[1] The apple-ring acacia (*Faidherbia albida*) is a leguminous tree appreciated for its ability to fix nitrogen in soils and it has been reported to contribute to increased yields of crops such as maize, sorghum and millet (CFU, 2007).

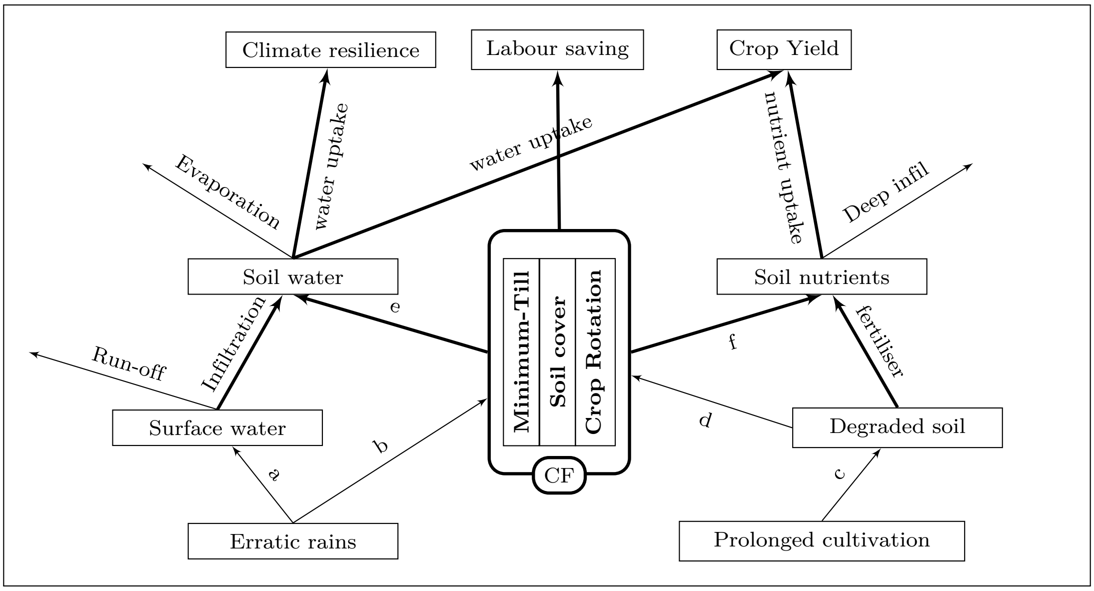
that CF is "the best on-farm solution to adapt to climate change" (CFU, 2012). This study therefore looks at CF from a climate adaptation perspective.

4.2.2 Effects of CF adoption on yield and climate resilience

Overall, conservation farming seeks to reduce labour input, increase yields and, more importantly, boost resilience to rainfall variability (Manda et al., 2016). A theory of change (TOC) in figure 4.1 is used to demonstrate how the adoption of conservation farming is hypothesised to impact on the three outcome variables.

Labour savings are generated from the employment of minimum tillage methods (Hobbs et al., 2008), while the use of cover crops and crop rotation seeks to improve soil structure, and to make more efficient use of water and nutrients (Koppmair et al., 2017; Tilman et al., 2002). This is envisaged to lead to improved yields as well as to reduce crop stress in times of low precipitation, and reduced waterlogging in wet spells (CFU, 2012). Nyanga et al. (2011) also reported that farmers perceive CF adoption to be advantageous in times of rainfall stress. This can also be referred to as climate resilience.

Figure 4.1: CF adoption Theory of Change



Source: adapted from Brouder and Gomez-Macpherson (2014) and Rusinamhodzi et al. (2011).

In figure 4.1, the adoption of CF is influenced mainly by two factors. First, CF is adopted in response to reduced or erratic rainfall (b). Secondly, CF is adopted in order to help improve the soil quality through the harnessing of legumes' nitrogen-fixing properties (d). The adoption of CF then leads to improved soil water (e) and nutrients (f) by minimising evaporation and improving soil structure. The improved soil water and nutrients enhance both resilience to rainfall variability and yields.

Therefore, the effectiveness of CF adoption can be assessed on the three fronts above. CF can first be examined to determine the extent to which it helps save labour. This would rely on comparing the labour demands of conventional farming methods to CF methods of cultivating or producing a given quantity of a crop (Montt and Luu, 2018).

The second front would involve examining the impact of CF adoption on farm yield. The central question here is to determine whether farmers who adopt CF methods are able to realise improved yields, compared to non-adopters. Does CF adoption lead to increased yields? In order to address this question adequately, circumstances or conditions under which CF leads to higher yields and when it fails to do so also need to be examined.

The third aspect involves examining the extent to which CF adoption builds climate resilience. Climate resilience can be viewed from different angles. It can refer to the ability of a farming systems to cope with erratic weather/rains or precipitation extremes which are caused by the changing climate (Antle et al., 2018; Ngoma et al., 2017). The Intergovernmental Panel on Climate Change (IPCC) defines climate resilience as implying reduced vulnerability to climate variability and extremes, where vulnerability is defined as the degree to which a farming system is susceptible to and unable to cope with adverse effects of climate variability and extremes (Lal et al., 2001, p995).

In the above definition, vulnerability has both external and internal dimensions (Antle et al., 2018; Fussel and Klein, 2006). The external dimension refers to exposure to some external shock. That is, farmers are considered vulnerable if they experience the effects of climate variability, such as precipitation extremes. On the other hand, the internal dimension refers to the inbuilt sensitivity or adaptive capacity to the effects of rainfall variability. Farmers are considered vulnerable if they lack the resources, knowledge or technology that are needed to cope with or adapt to the changed climate. Conservation Farming, theoretically, is expected to be less vulnerable to rainfall variability than conventional farming methods. Yields under CF should not suffer as much as yields under conventional farming methods when there are precipitation extremes such as droughts or excess rains.

Three areas of evaluation are presented: impact on labour saving, impact on crop yield, and impact on climate resilience. However, this chapter will only look at the last two. That is, it will (1) examine the effectiveness of CF in increasing yields, and (2) examine the impact of CF adoption on in building climate resilience among smallholder farmers. The impact of CF adoption on labour saving could not be evaluated because of a lack of appropriate data.

4.3 Literature Review

A number of studies have attempted to evaluate the impact of CF adoption for increasing yields and building resilience to rainfall variability, with varying results. For instance, Michler et al. (2019) and Montt and Luu (2018) have found positive results of CF adoption only in the long run, while others, such as Hobbs et al. (2008), Kuntashula et al. (2014), and Naab et al. (2017), note that the impact of CF adoption is region-specific and will depend on factors such as prevailing climate, soil type, and cropping systems, which are known to vary from one region to another or one country to another.

For instance, Abdulai (2016) and Kuntashula et al. (2014) found a significant positive effect of CF adoption on yields in Zambia, while Abdulai and Huffman (2014) found a positive impact of CF adoption on rice yields in Ghana. In Ethiopia, Tessema et al. (2015) found that CF adoption improved maize yields but not the stability of yields across different climate scenarios. In Zimbabwe, Michler et al. (2019) found a positive correlation between yield and CF adoption, which however vanished on controlling for the endogeneity of CF adoption, and they concluded that farmers adopting CF realize higher yields in periods of rainfall stress compared to conventional methods. This finding was also supported by Busari et al. (2015), who pointed out that crops cultivated using the principle of minimum tillage were reported to be more resilient to harsh weather conditions than crops under traditional tillage methods. Corbeels et al. (2014) and Rusinamhodzi et al. (2011) used meta-analyses and found that a combination of no tillage and crop rotation has a significant positive weighted mean difference over conventional farming practices on crop yield.

Arslan et al. (2015) also looked at the impact of CF adoption on crop yield. They found no significant impact of minimum tillage, a positive impact of legume intercropping, and a negative impact of crop rotation on maize yield. Other studies found mixed results. For instance, Mango et al. (2017) only found a positive impact of CF adoption in Mozambique but no significant effect in Malawi and Zimbabwe. They argue that the effectiveness of CF in Mozambique could be due to concurrent adoption of better crop management practices, such as timely weeding and better seed varieties, which were initially hampered by past internal conflicts in the country. Although Naab et al. (2017) found no evidence to support zero tillage over conventional tillage methods as the latter outperformed the former, they nonetheless concluded that zero tillage has more than double the return to labour compared to conventional tillage.

This section reviews the literature in order to identify gaps. The section is divided into three key issues in the literature: the econometric approaches in the literature (subsection 4.3.1);, types of data used in the literature in (subsection 4.3.2), and the definition and measurement of variables in (subsection 4.3.3).

4.3.1 Econometric Approaches in the Literature

A number of approaches have been proposed and employed to estimate the impact of CF adoption on crop yields and resilience to variability in climatic variables. These include the ordinary Cobb-Douglas formulations using a dummy indicator variable (Asfaw et al., 2017; Michler et al., 2019; Suri, 2011), the endogenous treatment regressions (Abdulai and Huffman, 2014; Di Falco et al., 2011; Kassie et al., 2015b; Lee, 1982; Manda et al., 2016; Teklewold et al., 2013b), and quasi-experimental designs (Mango et al., 2017).

For instance, Naab et al. (2017) used a two stage-experimental design to estimate, among other things, the impact of CF adoption on crop yields in Malawi. In the first stage, they experimented with three tillage methods: tractor plough, manual hoeing, and no tillage. In the second stage, under each tillage method, they experimented with three cropping systems: maize monocropping, soybeans/maize rotation, and soybeans/maize intercropping.[2] Randomised experimental methods are appreciated for their ability to identify the causal effect. However, the design and the results may not always mimic real-life situations (Carey and Stiles, 2016).

Mango et al. (2017) used the average treatment effect (ATE) framework, using the nearest-neighbour approach based on the work of Rosenbaum and Rubin (1983). Kuntashula et al. (2014) used the ATE framework with propensity score matching based on Rubin (1974). These methods may be marred with endogeneity problems due to the non-random assignment of subjects to treatment. When the assignment to treatment is not randomized, there may be systematic differences between the treated and control groups. Nonetheless, Rosenbaum and Rubin (1983) have shown that even under such circumstances, when conditioned on observable explanatory variables X, the assignment to treatment can be considered unconfounded. Consequently, the nearest-neighbour approach, which matches observable characteristics, can be used to estimate ATE without bias (Sekhon, 2010). The major challenge is to identify variables that cure the problem of confoundedness. The method also relies on the parallel trends assumption, which does not always hold (Fredriksson and Oliveira, 2019; Stuart et al., 2014).

As an alternative, Michler et al. (2019) used a Cobb-Douglas model to estimate the effect on yield of adopting minimum tillage in the context of rainfall variability. They estimated a model of the form:

$$y_{kit} = \beta_k CF_{kit} + \theta_k RD_{it} + \phi_k RD_{it} CF_{kit} + X_{jkit}\gamma_{jk} + \tau_i + \delta_t + \epsilon_{kit}, \tag{4.1}$$

where X_{jkit} is a vector of inputs, τ_i is the time-invariant household effect calculated on the basis of the *Mundlak-Chamberlain* device (Wooldridge, 2010). The Mundlak-Chamberlain device, based on the works of Mundlak (1978) and Chamberlain (1984), permits using time averages $\bar{X}_i$ of observable choice variables in place of the unobservable time-invariant household effect τ_i. The model also includes year dummies δ_t to control for time-variant fixed effects.

The usage of CF is captured by a dummy variable CF_{kit} and β_k is the associated measure of CF impact on yield. Michler et al. (2019) used the number of households receiving subsidised inputs as part of Zimbabwe's protracted relief programme (PRP) as the instrumental variable for the adoption of CF. The PRP was a four-year project aimed at providing short-term nutritional, economic, and agricultural interventions to smallholder households in Zimbabwe. The RD_{it} is the impact of a rainfall deviation, whose definition is shown later in eqn. (4.4), which they also interacted with the CF dummy in order to measure the effect of CF on yield resilience to rainfall variation.

[2] Intercropping is the practice of concurrently growing two or more crops in the same field, often in alternating rows or sections (CFU, 2007).

Abdulai (2016) used the endogenous switching regression (ESR) model discussed in the preceding chapter under eqn. 3.6, based on Lee (1978, 1982), to estimate the impact of CF technology on household welfare in Zambia. Others include Di Falco et al. (2011) who used the ESR to evaluate the impact of climate adaptation measures on food security in Ethiopia and Di Falco and Veronesi (2018) on the impact of climate adaptation on farm household's downside risk exposure in the Nile basin. The ESR has the advantage of estimating different models for observations in different states of adoption. It allows the estimation of the model for adopters and non-adopters. However, this model is more appropriate to assess whether individuals make the right decision to adopt or not to adopt, based on their characteristics, which may not be observable to the researcher. This is termed *selectivity bias*, that individuals who adopt will perform differently from those who choose not to adopt (Lee, 1978, 1982). Further, this model is designed for binary selection variables, while the adoption of CF is multi-category if one allows for partial adoption.

The alternative is the Multinomial endogenous treatment effects model (METEM) based on Deb and Trivedi (2006a,b) or the multinomial endogenous switching regression model (MESRM) employed by Kassie et al. (2015b) and Teklewold et al. (2013b). These models allow for multivalued treatments and are suitable to estimate the impact of CF adoption, which involve many bundles of CF principles. Manda et al. (2016) have argued that between the two (MESRM and METEM), the METEM is not only computationally easy but also allows the distribution of the endogenous treatment and outcomes to be specified using latent factor structure. Like the ESR model in eqn. 3.6, multinomial endogenous models consist of two stages. In the first stage, farmers choose to adopt one of the many possible combinations of practices. This choice is assumed to be based on an indirect utility from the bundle of practices adopted (Kassie et al., 2015b; Maggio et al., 2018; Manda et al., 2016). Based on Deb and Trivedi (2006b), let V_{ij}^*, the utility from the jth bundle be given by

$$V_{ij}^* = Z_i^{\prime}\alpha_j + \sum_{k=1}^{J} \delta_{jk} l_{ik} + \eta_{ij}, \tag{4.2}$$

where Z_i is a vector of exogenous covariates with the corresponding vector of parameters α_j and η_{ij} are assumed to be independently and identically distributed error terms. The l_{ik} is the latent factor which incorporate unobserved characteristics common to both adoption decision and outcomes such as individual farmer's abilities and technical knowledge (Abdulai and Huffman, 2014; Manda et al., 2016). In the second stage, the impact of the adoption decision on the outcome variable is given by

$$E(y_i|d_i, X_i, l_i) = X_i^{\prime}\beta + \sum_{j=1}^{J} \gamma_j d_{ij} + \sum_{j=1}^{J} \lambda_j l_{ij}, \tag{4.3}$$

where X_i is a vector of exogenous covariates and d_{ij} denotes observed adoption decision. The parameters γ_j denote the treatment effects of adopting the jth bundle relative to no adoption. The METEM corrects for the endogenous selection into treatment and produces consistent estimates of the treatment effects (Kassie et al., 2015b; Maggio et al., 2018; Manda et al., 2016).

This subsection has highlighted a number of estimation methods that are available for the problem at hand, albeit with varying appropriateness. The RCT, in particular, is not suitable because of the structure of the available data. Similarly, the ESR does not permit a multivalued selection variable. This chapter, therefore, builds on the Cobb-Douglas model used by Michler et al. (2019).

4.3.2 Data in the Literature

Most studies evaluating the impact of CF adoption on crop yield and resilience to climate variability have relied on panels of at least two waves. For instance, Arslan et al. (2015) used two rounds (2004 and 2008) of the Rural Incomes and Livelihoods Surveys (RILS) in Zambia. RILS were supplemental surveys to nationally representative 1999/2000 Post-Harvest Surveys. Similarly, Michler et al. (2019) used a four-wave (2007-2011) panel of farming households in Zimbabwe. The data were collected as part of a broader study by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) and were considered to be nationally representative of smallholder farmers in Zimbabwe.

Some studies relied on regional cross-sectional datasets that mimicked randomised controlled trials. For instance, Abdulai (2016) surveyed 408 smallholder households in the Central, Eastern, Southern, and Western provinces of Zambia, which account for more than 60% of the country's maize output. A multi-stage sampling procedure was used, ranging from province to district, agricultural camp, and farmers' group. In each farmer group, a comparable number of CF adopters and non-adopters was selected. In the case of Mango et al. (2017), a subset of 1,623 households interviewed during the Forum for Agricultural Research in Africa was used. These were cross-country data, covering north-eastern Zimbabwe, the central region of Mozambique, and the southern part of Malawi. Other studies, such as Lalani et al. (2017), were based on a sub-national survey of 197 farmers from the Metuge district of Mozambique, supplemented with qualitative data from key-informant interviews and focus group discussions.

From the foregoing, it can be seen that studies relied on mostly two-wave panels in order to estimate the impact of adopting CF. Two-wave panels offer both cross-sectional and time advantages in impact evaluations. This chapter uses a two-wave nationally representative panel of rural households.

4.3.3 Key Variables in the Literature

This subsection discusses the definition and measurement of key variables in the estimation of the impact of CF adoption on crop yield and resilience to rainfall variability and identifies areas for improvement.

4.3.3.1 Rainfall deviation

Rainfall remains an important determinant of yield in rain-fed agriculture (Arslan et al., 2014; Branca et al., 2013; Jain, 2007; Kassie et al., 2013; Lal et al., 2001; Rusinamhodzi et al., 2011). The rainfall deviation is usually computed in line with Ward and Shively (2015) as a normalised deviation from the expected seasonal rainfall over a fifteen-year period. The rainfall deviation for a particular location w in period t was given in eqn. 2.16 as:

$$RD_{wt} = \frac{r_{wt} - \bar{r}_w}{\sigma_{r_w}}, \tag{4.4}$$

where r_{wt} is the observed amount of rain in the season and location, $\bar{r}_w$ is the average rainfall for the location over the period, and σ_{r_w} is the standard deviation of seasonal rainfall over the same period.

However, the current literature shows a lack of inclusion of objectively measured rainfall deviation in models of yield and other outcome variables, such as the adoption of climate-smart agricultural principles. Although Michler et al. (2019) employed the rainfall deviation defined in eqn. 4.4, their rainfall data were only available at ward level.

Other studies, such as Behnke et al. (2018), applied the drought severity index (DSI) to rice production, based on Mu et al. (2013). The DSI is a dimensionless index, ranging from negative infinity for drier than normal and infinity for wetter than normal. The two measures of rainfall extremity are similar, with positive values indicating higher rainfall and negative values indicating low rainfall, and both are in comparison to the long-term established averages.

However, both fail to capture within-season maldistribution of rainfall. For instance, the newly introduced weather-indexed crop insurance scheme running alongside the farmer input support programme (FISP) defines bad weather conditions both in terms of overall seasonal rainfall and within-season distribution. The measure of rainfall deviation or more appropriately *precipitation extremity* in the weather-indexed insurance scheme differentiates between early and late droughts, as well as between droughts and excessive rains, and permits the occurrence of all three in one season. That is, it is possible to have a dry spell that negatively affects crops and concentrated, excess rainfall over a short period, so that over the entire season, the cumulative rainfall is normal. It is also possible to have below-normal seasonal rainfall that is well spread over the season, resulting in a minimal negative impact on crop. This maldistribution cannot be captured by the formulation employed by Michler et al. (2019) in eqn. 4.4 and calls for better designed measures of rainfall extremity or deviations.

4.3.3.2 CF adoption

The literature is unanimous on what constitutes the adoption of full CF. However, there still remain variations on what is considered partial adoption. Generally, two schools of thoughts emerge. One takes CF as the ultimate goal, beginning with the adoption of MT, then adding soil cover to become conservation tillage, and ultimately CF when crop rotation is added (CFU, 2012). This has also been referred to as the sequential adoption of CF principles and places the emphasis on the order in which principles are adopted, often emphasising the inclusion of MT (Lalani et al., 2017; Tessema et al., 2015; Zulu-Mbata et al., 2016). The CFU (2012), in its extension services, emphasises the minimum tillage, conservation tillage, and conservation farming (MT-CT-CF) sequence of adoption.

Another school of thought regards partial adoption of CF as the adoption of fewer principles than are in full CF. This definition does not consider the sequence or the composition of the subsets. The degree of adoption is measured simply by the number of principles that a farmer implements (Andersson and D'Souza, 2014; Arslan et al., 2014; Baudron et al., 2007; Pedzisa et al., 2015b). This definition is open and allows initial adoption to start with any of the three principles. As will be shown later, a large proportion of farmers actually start with either crop rotation or soil cover, and not with minimum tillage as required by CFU (2012). This chapter follows the broader view of CF adoption.

4.4 Methodology

There are two ways to assess the benefits of CF adoption to farmers. The first approach is to look at how CF adoption impacts crop yield. This involves comparing the yields of farmers employing different combinations of CF to those of farmers employing traditional farming methods. This comparison can also be done at plot level, comparing fields managed along CF principles and those cultivated using traditional methods. This would provide an indication of how adopting CF affects crop yield.

The second approach is to look at how yield is negatively affected by bad weather, comparing CF adopters and non-adopters. The role of CF, at least in the short run, is to mitigate the negative impact of weather on crop performance or yield. Looking at how CF and non CF fields perform after an extreme weather episode will provide information on the effectiveness of CF for cushioning the negative impact on yield of extremes in weather. This would also involve comparing the degree or probability of crop failure between CF adopters and non-adopters. If CF is effective, CF adopters are expected to report less crop failure compared to non-adopters.

This section discusses the methodology employed, in three subsections. Subsection 4.4.1 discusses the econometric model used and subsections 4.4.2 and 4.4.3 look at data and the definition and measurement of variables, respectively.

4.4.1 Model Specification

There is some evidence already, as adduced in chapter 2, that the employment of CF is influenced by household (Z) and plot (P) characteristics (Arslan et al., 2014; Baudron et al., 2007; Habanyati et al., 2018; Zulu-Mbata et al., 2016). This means that the fields or plots to which CF is applied may not be comparable to fields on which conventional methods are used.

Farmers may choose to employ CF on plots that they know may not do well under conventional farming methods. Similarly, household characteristics may systematically differ between CF adopters and non-adopters. Households endogenously *self-select* into CF (Heckman, 1979; Kassie et al., 2015b) based on their known characteristics, as well as those of farm plots, which may not be observable to the researcher. This introduces potential endogeneity in the model.

Given these circumstances, this chapter employs the multinomial endogenous treatment effects model (METEM) based on Deb and Trivedi (2006a,b) and discussed in section 4.3. The model was also employed by Maggio et al. (2018) and Manda et al. (2016). This is a two stage model, where the first stage involves the farmer's adoption decision and in the second stage, the impact of adoption on outcome variables, here crop yield and resilience to extreme weather. The second stage model is developed from eqn. 4.3. The expectation of the outcome variable is

$$E(y_i|d_i, x_i, l_i) = X_i'\beta + \sum_{j=1}^{J} \gamma_j d_{ij} + \sum_{j=1}^{J} \lambda_j l_{ij}, \tag{4.5}$$

where x_i is a vector of exogenous covariates including inputs, household and field or plot characteristics that have the potential to impact the outcome variable including a year fixed effect. The model includes a measure of rainfall deviation because this is a rain-fed agricultural setting, rainfall plays a critical role in determining output or yield. For instance, dry spells and/or flooding have negatively affected the harvests realised by smallholder farmers, whose production systems are dependent on rains.

The d_{ij} is the observed adoption defined later in section 4.4.3.2. The parameters γ_j will measure the treatment impact of adopting the jth bundle, relative to none adopted. The inclusion of inputs, mainly fertiliser per hectare, in the regression is important to control for possible variations in the use of inputs between CF and non-CF fields. Baudron et al. (2007) noted that some of the yield differences attributed to CF adoption actually occur because of the higher input use that is strongly recommended under conservation farming. The use of unobservable and observable plot level heterogeneity including land quality and inputs is proxied using the quantity of fertiliser per hectare. Kassie et al. (2015b) have argued that farmers can use their private knowledge of unobservable effects such as soil quality to adjust factor inputs. The l_{ij} corrects for the endogenous selection to treatment or unobserved heterogeneity between treated and control fields.

The METEM corrects for the endogenous selection into treatment and produces consistent estimates of the treatment effects (Kassie et al., 2015b; Manda et al., 2016). The outcome variables are defined later in section 4.4.3.1. Although not a strict requirement for identification, the regression will include covariates in the treatment equations that do not feature in the outcome equation in line with Deb and Trivedi (2006a) and Manda et al. (2016).

4.4.2 Data

The primary data for this chapter are the Rural Agricultural Livelihood Surveys (RALS) described in section 1.3.1. This chapter will use the unbalanced panel of 16,773 household observations. The surveys also have plot-level[3] data on land use and management, as well as crop management, including any application of conservation farming principles, the area of planted field harvested, the quantity of crop harvested, and the reasons for not harvesting the whole planted area. This gives 46329 crop-field level observations, allowing the regression of crop outcomes at plot a level. The RALS data is combined with CHIRPS rainfall data, a high-resolution satellite rainfall data discussed earlier in section 1.3.3. Each farmer is assigned rainfall measurements from the nearest satellite point.

4.4.3 Operational Definitions of Variables

This section provides conceptual and operational definitions of the main variables as they are used in this chapter.

4.4.3.1 Dependent variables

The chapter employs two dependent variables: crop yield and climate resilience. Crop yield is computed at plot level as the amount of crop in kg per hectare planted. Climate resilience is measured using the downside risk, based on the skewness of yield in line with Di Falco and Veronesi (2018) and Kassie et al. (2015b). An intervention is said to improve resilience if it significantly increases yield skewness (or reduces the probability of crop failure). This method is widely used in the literature and is argued to capture a broader extent of risk exposure (Di Falco and Veronesi, 2018).

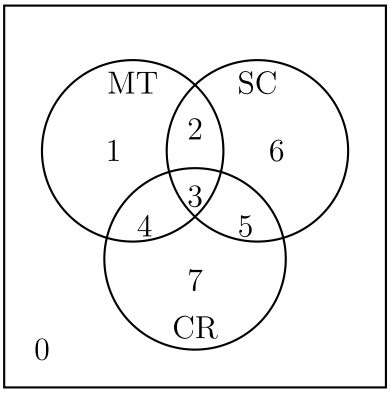
4.4.3.2 CF adoption

The chapter defines CF adoption at plot level based on the combination of principles adopted, as illustrated in figure 4.2.

The value of zero represents fields on which no CF principle was applied. The first three numbers represent the MT-CT-CF route which emphasises MT as the initial principle of CF, as defined by CFU (2012). The fourth number represents the combination of MT and CR, but without SC. The last three numbers (5,6 and 7) represent the use of SC and CR in combination or isolation. This definition permits the estimation of the effects of different combinations of CF principles.

[3] Data were collected, for each crop field, on land management practices such as tillage methods, crop rotation, and the quantity of crop harvested.

Figure 4.2: The discrete labels of CF adoption



4.4.3.3 Rainfall deviation

The chapter measures the first order mean rainfall deviation RD^* as the standardised deviations from long-term averages, based on Michler et al. (2019) and Ward and Shively (2015).

$$RD^*_{it} = \frac{r_{it} - \overline{r_i}}{\sigma_i}, \tag{4.6}$$

where r_{it} is the rainfall measurement for the ith farmer in year t, $\overline{r_i}$ is the long-term average rainfall at the location of farmer i, and σ_i is the respective standard deviation. The rainfall deviation is computed using rainfall values for December, January and February only, because these are the critical rainfall months in Zambia (CFU, 2007; Jain, 2007). The measure has the advantage of capturing deviations of rainfall from established averages but also distinguish positive from negative deviations. This definition of the rainfall deviation also deviates from the one defined for chapters 2 (*see* eqn. 2.26) and 3 (*see* eqn. 3.18) because while these chapters were concerned with farmers' response to rainfall variability, this chapter is concerned with crop response.

4.4.3.4 Human capital

Household size is measured as the number of adult members, defined as members aged 15 or above, while gender is the proportion of males among the adult household members. Households are considered male dominated if the proportion of males exceeds 50%. Level of education refers to the highest level of education, in years, attained by any adult member of a household, while training indicates the receipt of CF-related training by any member of a household.

4.4.3.5 Social capital

Social capital or social networks are binary measures of membership in agriculturally-oriented farmers' organisations or groups by any member of the household. Respondents provided information on membership in farmers' cooperatives, women's groups, and local savings and loans societies (lsls).

4.4.3.6 Physical capital

Physical capital affects the level of investment made on each field plot. In this chapter, physical capital is measured as the number of major farming assets that a household owns. For instance, 'cattle' is the number of cattle owned, 'plough' is the number of ox-drawn ploughs owned, and 'sprayer' is the number of knapsack sprayers owned. Quantities are better than binary indicators of ownership because quantity provides more detail on the level of ownership.

4.4.3.7 Plot/field characteristics

Plot characteristics, such as location in wetlands, prone to flooding, etc., have the potential to affect crop success and resilience to weather extremes and are important controls for plot level analysis of yield and climate resilience. In this chapter, 'hectarage' is the size of the field-plot in hectares, 'distance' is the distance of the field from the homestead, 'dambo' is a binary indicator of whether the field is located in a wetland or not, and 'floods' is a self-reported indicator of whether the field-plot is prone to flooding.

4.5 Empirical Analysis

This section discusses the results in two subsections. Subsection 4.5.1 provides descriptive analysis and subsection 4.5.2 presents a discussion of the findings.

4.5.1 Descriptive Analysis

This section provides some descriptive analysis of selected variables. In particular, the section discusses household characteristics and the ownership of farming assets, levels of adoption of CF, crop performance, and causes of crop failure.

4.5.1.1 Household characteristics

Household characteristics, such as demographics and the ownership of farming assets, shape household decision-making and the ability to achieve or execute farming tasks. Consequently, outcome variables in this chapter are also likely to be influenced by household characteristics, hence the need to understand these characteristics in the sample. Table 4.1 gives descriptive statistics of selected household demographic, social, and economic variables.

The average age of household heads was 47 years with a high standard deviation. The youngest head was only 17 years, while the three-sigma upper limit was 91 years.[4] The head of household aged 17 or slightly over is a manifestation of the existence of child-headed households which the CSO (2012) estimates to comprise about 0.9% of all households in Zambia. Extreme ages on the right are a manifestation of the Zambian culture, where the eldest member is the head of

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[4] The actual maximum age in the data was 111 years, and there are a number of other cases where age exceeds 100 years. However, these are rare extremes and hence the three-sigma limit was used instead.

Table 4.1: Household characteristics

Variable	obs	mean	sd	min	max
age	12,628	47.200	14.500	17	91*
gender (male=1)	12,628	0.470	0.187	0	1
household_size	12,628	3.800	2.020	1	21
education	12,628	8.090	3.010	0	18
assets ownership					
-cattle	12,628	0.336	0.472	0	1
-plough	12,628	0.276	0.447	0	1
-ripper	12,628	0.034	0.180	0	1
-sprayer	12,628	0.213	0.410	0	1
-tractor	12,628	0.004	0.067	0	1
membership in					
-cooperative	12,628	0.535	0.499	0	1
-women group	12,628	0.241	0.428	0	1
-loans/savings group	12,628	0.050	0.217	0	1
-any_farmer group	12,628	0.589	0.492	0	1

**=based on three-sigma (3σ) limit*

the household, even when they may no longer exert any influence on decision making. Gender composition shows that males, on average, comprise about 47% of household members. The number of adults in a household averages 4, with a minimum of 1 and maximum of 21 members, while the level of education is on average 8 years.[5]

The ownership of farming assets shows that farmers depend more on animal draught power than on mechanised means such as tractors. About 34% of respondents reported owning cattle, compared to 0.4% who reported owning a tractor. The major implements owned are an ox-drawn plough, at 28%, and a knapsack sprayer at 21%. The ownership of CF-enhancing implements, such as a ripper for minimum tillage, remains low. Only 3.3% of respondents owned a ripper.

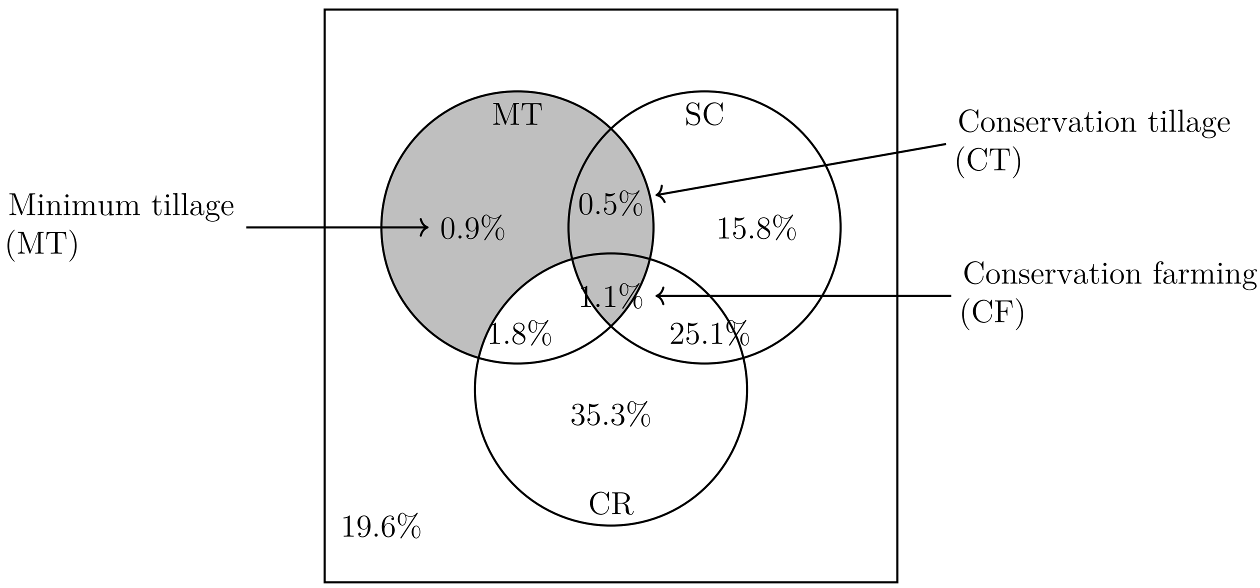
Membership in farmers' groups, such as cooperatives or loans and saving societies, provides an avenue for the sharing of information and transfer of knowledge among farmers. In addition, these groups are also the basis on which farmers receive external support, such as FISP and other extension services provided by both the government and its partners (CFU, 2012; MoA, 2012). However, membership does require payment of membership fees, which rural households cannot easily afford. Table 4.1 shows that 53.5% of respondent households had at least one member belong to a farmers' cooperative. Only 24% of households had at least one member belonging to a women's group, while membership in local savings and loan societies is low at 5% of respondent households. A further computation shows that only 59% of respondent households had membership in any of the three categories of farmers' groups. This suggest that more than 40% of households do not belong to any farmers' groups.

[5] In the Zambian education system, 8 years of education corresponds to the first year of secondary schooling.

4.5.1.2 Adoption of CF

Although farmers can choose to adopt any combination of the three principles of CF, the CFU (2012) defines particular combinations in its definition of gradual adoption. The CFU considers MT as the first principle, adding SC to become conservation tillage, and ultimately CR to complete conservation farming (CF), referred to in this chapter as *MT-CT-CF*. Figure 4.3 is the Venn diagram showing the number of farmers who reported having adopted different combinations of CF. The shaded area shows the MT-CT-CF route as defined by CFU (2012).

Figure 4.3: Venn diagram on adoption of CF principles



Using the MT-CT-CF progression, the figure shows that 422 (0.9%) fields were in the first step, having been under MT. Another 248 (0.5%) fields are considered to have been under conservation tillage, which combines MT and SC. Full CF was implemented on 528 (1.1%) fields only. The level of adoption of CF in the strict sense remain low, with about 1.1% of the fields having been cultivated under full CF.

Figure 4.3 shows that more farmers adopt CR and SC in isolation than they do MT. Restricting the CFU (2012) definition of the pathway to CF would exclude many cases where at least one principle of CF is practised. For instance, 16,927 fields (35%) were crop-rotated but neither of the other two principles was practised. Similarly, 12,072 fields (25%) were under both soil cover and crop rotation but with no MT implemented. These scenarios would not fit the CFU (2012) definition of partial adoption of CF because they do not start with MT. These numbers are generally lower than previously reported in other studies (see Arslan et al., 2014; Zulu-Mbata et al., 2016) because this chapter reports at plot level. A farmer may report employing all three principles of CF but on different plots. A household-level analysis will categorise such farmers as full adopters, while plot-level analysis will show partial adoption.

This chapter therefore takes partial adoption of CF as constituting the implementation of any subset of full CF, without placing emphasis on the inclusion of any particular principles. This is supported in the literature. Works such as Andersson and D'Souza (2014) and Pedzisa et al. (2015b) have argued for a broader definition of partial adoption.

4.5.1.3 Crop performance

Each household provided information on the hectarage of each crop planted and the hectarage harvested, the difference having failed. In order to assess the level of severity of crop failure, the area harvested is calculated as a proportion of area planted. The actual harvest is used to measure crop yield for each field. Table 4.2 presents information on crops cultivated, the resulting harvest and yield, and the major causes of crop failure. Sunn hemp (*Crotalaria juncea*) is included as a special crop, mostly used as fodder, organic soil cover, or green manure (Arslan et al., 2015; Florentin et al., 2010).

Table 4.2: Main crops grown and their performance

	Crop performance					Cause of failure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
crop	% of farmers	mean hectarage	% ha harvested	yield kg/ha	value ZMW	rain related	lacked inputs	other causes
Maize	92.7	1.29	86.3	2315	3806	28.7	42.5	28.8
Sorghum	4.2	0.61	85.0	742	554	50.3	5.4	44.3
Rice	6.3	0.7	82.1	1390	1218	49.2	11.8	39.1
Millet	9.2	0.42	92.5	871	406	46.9	14.0	39.1
Sunflower	12.1	0.5	94.9	573	464	25.5	5.4	69.0
Groundnuts	55.3	0.37	92.7	670	686	33.1	6.3	60.7
Soybeans	7.7	0.58	93.2	869	1162	28.2	9.4	62.4
Seed cotton	16.3	1.08	93.6	1077	2845	36.6	2.3	61.1
Irish potato	0.4	0.35	96.4	6404	2135	20.0	20.0	60.0
Tobacco	1.8	0.73	97.4	1410	6128	27.8	16.7	55.6
Mixed beans	17.7	0.43	94.2	531	841	33.1	9.1	57.8
Popcorn	0.7	0.81	93.1	1082	1385	23.5	29.4	47.1
Sunn hemp	0.01	0.09	100.0	300				
At least one crop	96							

Column 1 has the percentage of farmers cultivating at least one plot of each crop. The table shows that most households (92.7%) grow maize. Other notable crops include groundnuts, grown by 55% of farmers, mixed beans, and cotton grown by 17.7% and 16.3% of farmers, respectively. Alternative cereals such as sorghum, rice, and millet are only grown by 4.2%, 6.3%, and 9.2% of respondent farmers, respectively and often in selected regions. The cultivation of sunn hemp remains extremely low, at about 0.01%. Overall, 16,111 reported cultivating at least one field crop, representing 96% of the sample.

Column (2) presents the average hectarage committed to each crop. The average hectarage of maize is highest at 1.29ha per household, indicating that smallholder farmers commit most of their land to maize cultivation. Cotton is next at 1.08ha per household. Although groundnuts were noted as being grown by the majority of respondents (55%), the average hectarage is low at 0.37. Other crops are grown by few farmers but on large areas. These include popcorn and tobacco, which are mainly grown as cash crops.

Column (3) has the percentage of plant area that was harvested and column (4) has the yield. This shows the proportion of the crop that survived and was ultimately harvested. The major causes of failure are presented and discussed in columns (6-8). Crop failure seems highest among cereals. For instance, on average, only 82% of rice hectarage is harvested, 85% for sorghum and 86% for maize. The other crops have success rates above 92%, with tobacco being as high as 97%.

The realised value of the crop in Zambian kwacha (ZMK)[6] is presented in column (5). The value of the crop is calculated as a product of total harvest and the reported price. In cases where the household did not report any price, the average for the cluster is used. This is common in cases where the household did not have a marketed surplus. If the price is not available at cluster level, then a district average or ultimately the provincial average was used. Crop value is important in order to give an indication of the relative importance of each crop to the smallholders' economic welfare.

The value of crops shows which crops are important in terms of revenue or consumption for the farming household. Tobacco is the highest-valued crop, at an average of $K6,128$ ($\approx US\$1,137$) per cultivating household, followed by maize at $K3,806$ ($\approx US\$706$) and cotton at $K2,845$ ($\approx US\$528$). Other crops of high value include Irish potatoes, popcorn, rice, and soybeans. These are the main crops that smallholders grow. When the value is weighted by the percentage of growers, the top three crops are maize, cotton, and groundnuts.

As shown in column (3), crop failure is reported across all the major crops, with varying causes. Columns (6-8) show the main reasons that farmers listed as having caused the failure of the portions of fields that were ultimately not harvested. The reasons are fragmented but can be broadly categorised into weather-related, lack of inputs, mainly fertiliser, and other causes, such as limitations in manpower for weeding.

The table shows that climate-related hazards such as droughts, heavy rains, floods, or waterlogging are frequent causes of crop failure. These account for 28.7% of failed maize fields and as high as half of the failures in other cereals (50.3% of sorghum and 49.2% of rice). This large a proportion of crop fields still succumb to weather extremes. This shows how high the level of vulnerability to rainfall variability is among smallholder farmers and the serious need to strengthen climate resilience. Lack of appropriate inputs, mainly inorganic fertiliser and hybrid seed, accounted for about 42.5% of maize failures and 29.4% of popcorn. Other causes are natural ones, such as destruction by animals and birds or by pests and diseases.

6 During the period of this study, the kwacha-dollar exchange rate was around: $US\$1 = ZMK5.39$.

4.5.2 Results and Discussions

This section provides an empirical analysis of the data. The section is divided into two subsections, in line with the specific objectives. Section 4.5.2.1 looks at the impact of CF adoption on crop yield while section 4.5.2.2 analyses the impact of CF adoption on mitigating the negative effects of precipitation extremes.

4.5.2.1 The Impact of adopting CF on crop yield

The chapter measures the impact of CF adoption on crop yield using the multinomial endogenous treatment effects model in eqn. 4.5. Treatment is the adoption of different combination of CF principles, as defined in figure 4.2. The regression results are presented in table 4.3.

Column (1) has results for the full sample. Column (2) focusses on cereals, which include maize, sorghum, millet, and popcorn, while column (3) has regression results on maize only. In most of sub-Sahara Africa and Zambia in particular, food security is determined by the production of basic cereals, predominantly maize, due to market weaknesses and subsistence orientation among smallholders (Asfaw and Davis, 2018; Kassie et al., 2015b). A comparison of sample sizes in columns (2) and (3) of table 4.3 shows that maize constitutes about 79% of cereals in the regressions. In addition, the adoption of CF is concerned mainly with the yield of cereals or staple crops (Mango et al., 2017; Pedzisa et al., 2015b), which in the case of Zambia narrows down to maize. This is the reason for focussing on cereals and maize only. Column (4) has results for category A farmers. These cultivate less than $2ha$ of land, are known to be more subsistence-oriented, and rarely own large livestock such as cattle, pigs or sheep, compared to, for instance, category C farmers (MoA and MFL, 2016, p. 7). In all the four columns, the dependent variable is the natural log of yield. The regressions also include indicator variables for crop type, but not shown in the table.

The results show that most combinations are significantly positive. This suggests that the adoption of different combinations of CF principles is associated with increased yield, save for CF_1 (MT only) and CF_2 (MT and SC) which are insignificant and CF_6 (SC only) which is negative. SC in the absence of CR may harbour pests and diseases and has been found to be negatively correlated with successive crop yield in the literature (Baudron et al., 2007; Manda et al., 2016).

The coefficients of these components are also mostly higher in cereals and maize than they are in the overall regression. This may support the prior notion that CF is perceived to be more beneficial with cereals, particularly maize, in Zambia. Its impact is more pronounced in the two regressions focussing on cereals and maize. This has also been observed in other studies, such as Mango et al. (2017) and Pedzisa et al. (2015b), that noted the increased importance of CSA practices on cereals.

The importance of the amount of rainfall in rain-fed agriculture is well-established (Lee and Thierfelder, 2017; Maggio et al., 2018; Tessema et al., 2015). As smallholder farmers rely on

Table 4.3: The impact of CF adoption on crop yield

VARIABLES	(1)	(2)	(3)	(4)
	All	Cereals	Maize	Category A
Dependent variable[1]	ln(yield)	ln(yield)	ln(yield)	ln(yield)
CF category[2]				
_1	0.073 (0.077)	0.068 (0.082)	0.182* (0.093)	0.059 (0.114)
_2	-0.014 (0.127)	0.010 (0.086)	0.032 (0.080)	-0.132 (0.135)
_3	0.135** (0.056)	0.274*** (0.080)	0.193*** (0.074)	0.250*** (0.086)
_4	0.188** (0.085)	0.342*** (0.072)	0.208** (0.102)	0.357*** (0.113)
_5	0.221*** (0.046)	0.251*** (0.043)	0.137** (0.061)	0.193 (0.125)
_6	-0.124*** (0.042)	-0.214*** (0.046)	-0.176*** (0.051)	-0.048 (0.076)
_7	0.257*** (0.048)	0.174*** (0.055)	0.182*** (0.058)	0.084 (0.068)
rainfall deviation	0.019*** (0.005)	0.015** (0.007)	0.012* (0.007)	0.011 (0.006)
plot characteristics				
_fertiliser	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
_dambo	0.017 (0.021)	-0.018 (0.028)	-0.050* (0.030)	-0.036 (0.041)
_hectarage	-0.046*** (0.008)	-0.002 (0.008)	0.019*** (0.006)	-0.266*** (0.037)
household characteristics				
_age	-0.001** (0.000)	-0.001** (0.001)	-0.001** (0.001)	-0.002*** (0.001)
_gender (male=1)	0.041 (0.031)	0.064 (0.041)	0.053 (0.040)	0.119*** (0.042)
_size	-0.001 (0.003)	-0.005 (0.005)	-0.004 (0.005)	0.015** (0.006)
_education	0.017*** (0.002)	0.014*** (0.003)	0.014*** (0.003)	0.009** (0.004)
_cattle (number)	0.001** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.001 (0.001)
year_2015	0.097*** (0.017)	0.015 (0.022)	0.000 (0.025)	0.062** (0.027)
Constant	6.833*** (0.051)	6.890*** (0.055)	6.897*** (0.053)	7.055*** (0.083)
Observations	34,431	14,717	11,632	11,857

SEA clustered robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

[1] ln(·) is the natural log.
[2] CF categories are as defined in figure 4.2 on page 125.

rain-fed agriculture, their yields are affected by the amount of rainfall received per season. The coefficients on rainfall (as defined in eqn. 4.4) are positive and highly significant. Higher levels of rainfall is associated with higher yields and *vice-versa*. This speaks to the high level of dependence and vulnerability to weather fluctuations among smallholder farmers. Farmers are not able to provide alternative sources of water in times of precipitation deficits. Studies have already documented low levels of irrigation, especially among smallholder farmers in Zambia (Akayombokwa et al., 2015; Ngoma et al., 2017).

The results also include other important covariates, mainly plot and household characteristics. The results also show that fertiliser (measured as quantity of fertiliser per hectare) is highly significant across all the regressions. It is also worth noting that the absolute value is higher in the cereals and maize-only regressions.

Two field characteristics were examined: the field being in a dambo and its size in hectares. Fields that are prone to flooding tend to have lower yields. The importance of field size is less clear. The coefficient is positive and highly significant in the maize-only regression, but negative in the other regressions. For fields committed to maize, larger fields tend to receive more attention. The results could also suggest that farmers have a tendency to pay more attention to maize, the main staple crop, possibly at the expense of other crops. For other crops, larger fields may receive limited attention, leading to lower yields.

Household characteristics, such as age of the household head, gender composition, household size, and the level of education have varying effects on yield. The age of the head of household seems to be negatively associated with the realised yield. The results shows that yield could be falling by about 0.1% for every additional year (or 1% for every decade) in age. Gender composition is significantly positive among category A farmers. Household size is also significantly positive in the same regression. Among category A farmers, households dominated by males tend to have higher yields compared to similar households dominated by females, and bigger families higher yields compared to households with fewer members. Bigger households enjoy a larger pool of available labour, while gender disparities indicate that males tend to have better access to the resources and information necessary to improve crop yield (Chompolola and Kaonga, 2016; Kassie et al., 2013; Pedzisa et al., 2015b). Category A farmers are the lowest in terms of landholding and obviously face more obstacles to CF adoption than other categories of farmers. They are more likely to rely on household resources for human and physical capital, and these resources are affected by gender and number of members. Households with higher levels of education tend to realise higher crop yields than households of low education. The coefficient on education is highly significant in all the four regressions. An additional year of education in a household can lead to more than 1% increase in crop yield.

The number of cattle owned is positively related to yield, although this is not significant among category A farmers. Cattle is a source of draft power (Chompolola and Kaonga, 2016; Habanyati et al., 2018) and also a measure of wealth especially among rural communities (Andersson and D'Souza, 2014; Antle et al., 2018). The results suggest that yield increases by 0.1 and 0.2% for every additional cattle owned.

4.5.2.2 Does CF improve climate resilience?

As shown in table 4.2, climate-related factors are a major cause of crop failure. The importance of CF is measured by how well it mitigates the negative impact of rainfall disturbances on crop yields and the probability of crop failure. When faced with a climate hazard, do fields on which CF was implemented have a better chance of survival than fields on which no CF was implemented? This is the central question in this subsection.

The downside risk, based on the third central moment of the error term is regressed on treatment T, the vector of CF adoption indicator variables defined in figure 4.2 and other control variables as in table 4.3 using the multinomial endogenous treatment effects model in eqn. 4.5. The treatmeent effects results are presented in table 4.4 while the full table is presented in appendix C as table C.2. Columns (1) is a regression on all crops, while (2) and (3) are based on cereals and maize only, respectively. As noted in section 4.5.2.1 above, food security in sub-Sahara Africa is mainly about the resilience of cereals, which in Zambia narrows down to maize (Asfaw and Davis, 2018; Kassie et al., 2015b; Mango et al., 2017; Pedzisa et al., 2015b). Column (4) has results for category A farmers, who cultivate less than $2ha$ of land mainly for subsistence and rarely own large livestock (MoA and MFL, 2016, p. 7).

Table 4.4: Impact of CF adoption on climate resilience

VARIABLES	(1)	(2)	(3)	(4)
	All	Cereals	Maize	Category A
dependent variable	skewness	skewness	skewness	skewness
CF category[1]				
_1	0.001 (0.088)	0.574** (0.288)	0.685** (0.326)	0.159 (0.106)
_2	0.356** (0.146)	0.268 (0.282)	0.258 (0.333)	0.048 (0.120)
_3	0.259 (0.677)	0.643** (0.251)	0.705** (0.291)	-0.258** (0.107)
_4	0.016 (0.118)	0.613** (0.240)	0.536** (0.249)	-0.045 (0.079)
_5	0.349** (0.174)	0.361** (0.154)	1.085*** (0.132)	-0.032 (0.089)
_6	0.216 (0.238)	-0.141 (0.101)	-0.131 (0.135)	0.106 (0.089)
_7	0.488*** (0.148)	0.152 (0.170)	0.086 (0.182)	-0.104 (0.093)
Observations	33,002	13,670	10,570	11,309

SEA clustered robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

[1] CF categories are as defined in figure 4.2 on page 125.

The adoption of CF is expanded into indicator variables, as set out in figure 4.2, comparing each combination of CF principles to ‘none adopted’. The results show that CF_1 (MT), CF_3 (Full CF), CF_4 (MT & CR) and CF_5 (SC & CR) are significantly positive. These are mainly significant in columns (2) and ((3)), which focus on cereals and maize. Crop rotation (CF_7) is also significant in the all-regression but insignificant elsewhere.

These results suggest that MT is effective in reducing the downside risk even when applied in isolation. MT enables especially resource constrained farmers plant early, which enables crops survive even shorter rainfall seasons (Arslan et al., 2015; Baudron et al., 2007; Grabowski et al., 2014; Nyanga et al., 2011). The results do not demonstrate any benefits from CR when applied in isolation. By nature, CR is meant to address long term soil quality issues and biotic stresses through disruption of pests and disease cycles (Corbeels et al., 2014; Florentin et al., 2010; Koppmair et al., 2017; Tilman et al., 2002). The definition of crop rotation used in this thesis, which is blind to the inclusion of legumes in the rotation, could also downplay the role of legumes in improving the soil structure.

On the overall, the adoption of different combinations of CF principles is tilted towards reducing vulnerability to the downside risk or crop failure. This has also been echoed by other studies, such as Di Falco and Veronesi (2018) and Kassie et al. (2015b), who found that the adoption of CSA does decrease the downside risk exposure (or leads to an increase in the skewness of the distribution of yield) among smallholders.

4.6 Conclusion

This chapter evaluates the impact of CF adoption on crop yield and resilience to rainfall variability at the plot level. An econometric approach was employed to estimate the impact of adopting CF on crop yield and the downside risk measured using the skewness based third central moment. A double hurdle multinomial endogenous treatment effects model was used to regress crop yield and skewness, respectively, on the adoption of conservation farming, and for other control variables. The chapter employed a rich combination of a two-wave nationally representative survey of rural households in Zambia (RALS) and a high-resolution satellite rainfall data. The combined data provide a unique opportunity to evaluate how weather conditions and CF adoption impact on climate resilience and yield at plot level.

The results show that the net impact of CF adoption on yield is positive. In particular, the chapter finds that different combinations of CF principles have a positive impact on yield. On preventing weather induced crop failure, the results show that CF in general helps to reduce crop failure. The results show that some combinations of CF principles do impact on crop yield distribution skewness, with potential to attenuate the negative impact of precipitation extremes on crop survivability.

In conclusion, the adoption of CF is advantageous to resource-constrained smallholder farmers depending on the prevailing microclimate. The chapter finds CF to be of value especially in low-rainfall settings. Therefore, the promotion of CF could be concentrated in AEZ I and selectively in AEZ II, where its impact will most appreciated. Promoting the adoption of CF in regions of high rainfall will lead to mixed results, which would jeopardize its adoption even in regions where it is critical to improving climate resilience. There is a need to move away from blanket policy prescriptions in agriculture to more targeted approaches that take into account the underling microclimate.

Part III

THE EPILOGUE

CHAPTER 5

CONCLUSIONS AND IMPLICATIONS FOR POLICY

Climate change and variability is a relatively recent global development challenge, the effects of which are global and cut across many sectors, from energy to agriculture and health. Although it remains a global problem, the effects are projected to be disproportionally felt by the poor in developing countries because these populations depend heavily on rain-fed agriculture and lack the resources needed to adapt adequately to the increased climate variability. Climate variability has resulted in declining and more erratic rainfall, threatening the livelihood of many rural populations of developing countries. In Zambia, rainfall has not only reduced in quantity but in duration also, with an increased occurrence of dry spells and droughts (McSweeney et al., 2012). Soil fertility has also declined, mainly from overuse and the use of environmentally unfriendly farming methods. This has contributed to declining farm productivity and revenue, leading to increased poverty levels especially in rural areas, and threatening the attainment of sustainable development goals pertaining to ending poverty and hunger.

In response, a number of measures have been proposed and are being implemented at global, continental and country levels. For instance, the African Union Agenda 2063[1] seeks to push for sustainable and climate-resilient communities by promoting investment in sustainable and climate-resilient farming methods. At the country level, the Zambian government developed a climate change response strategy which envisions the development of a sustainable land use system to enhance agricultural production and ensure food security. Specific strategies include support for early warning systems, crop diversification including the cultivation of indigenous and drought tolerant food crops, improving access to improved farm inputs, adoption of improved soil management practices such as conservation farming, and investment in water harvesting technologies to support irrigation. Consequently, the government and its partners have introduced measures to promote the adoption of conservation farming alongside other strategies, such as crop diversification and irrigation, as climate-adaptation strategies. Specific measures have included the setting up of institutions to provide technical support to farmers and the reform of the country's farmer input support programme (FISP) to broaden the number

[1] The African Union Agenda 2063 is Africa's strategic framework and includes inclusive and sustainable development goals. *See* note 3 on page 4.

of crops covered.

Despite these efforts to promote adaptation, evaluations have continued to show low levels of adoption, including some evidence of dis-adoption or abandonment, where farmers move away from previously-adopted strategies. This raises a number of questions, which this thesis has attempted to address. For instance, what are the drivers of the adoption of different adaptation strategies used by smallholder farmers? What has been the impact of policy reforms on smallholder farmers' adoption of climate-smart and sustainable farming practices? Do smallholder farmers find these climate-smart agricultural practices, with particular reference to conservation farming, beneficial? These questions have not been conclusively addressed in the existing literature. In addition, the agricultural sector is highly influenced by prevailing microclimates and farming cultures which necessitate locally generated evidence to inform policy.

This thesis therefore sought to investigate climate-change adaptation among smallholder farmers in Zambia using the Rural Agricultural Livelihood Surveys (RALS) as the main data source. The thesis approached the subject in a three pronged manner: (1) adaptation behaviour, (2) the role of policy, and (3) assessing the policy's appropriateness and effectiveness. In particular, the thesis pursued the following broad objectives, which also guided the three analytical chapters in Part II of the thesis:

- to determine factors that drive the adoption of different CC adaptation strategies among smallholder farmers.
- to determine the impact of the farmer input support programme reforms on smallholder farmers' adoption of climate-smart and sustainable farming practices.
- to examine the impact of the adoption of conservation farming on smallholder farmers' performance in the context of rainfall variability.

The three broad objectives above are tackled in the three analytical chapters, forming chapters 2, 3, and 4, respectively. Chapter 2 examined factors driving the adoption of climate-adaptation strategies such as extension services and exposure to precipitation extremes. The chapter employed a mixed-methods approach, combining econometric (seemingly-unrelated-regressions based probit, ordered probit and tobit) and qualitative methods. The chapter looked at adaptation at four levels: policy and options available, farmers' choice to adopt, number of strategies adopted or what is sometimes referred to as bundled adoption, and the intensity of adoption using the proportion of land on which the practice is applied. The chapter used a combination of the two-wave nationally representative RALS, satellite rainfall data, and primary qualitative data from in-depth interviews with agricultural extension workers in two rural districts of Zambia.

Chapter 3 evaluated the impact of the farmer input support programme (FISP) reforms on crop yield and the adoption of crop diversification and crop rotation as part of climate adaptation measures. The chapter employed the Neyman-Rubin model of treatment effect to isolate the impact of FISP reforms on crop yield, the degree of crop diversification, and intensity of crop rotation. The chapter combined a balanced panel subset of RALS and data on FISP allocations in the 2012/2013 farming season, providing a panel data with pre- and post-reform observations. This allowed the use of a combination of difference-in-differences, propensity weighting/matching and endogenous treatments effect methods. This combination of methods is able to control for both time-invariant unobservable effects and effects that are accounted by observable characteristics as well as the endogenous or criteria based assignment to treatment.

Chapter 4 investigated the effectiveness of conservation farming in increasing crop yield and resilience to rainfall variability at a plot level. The chapter defined climate resilience using the skewness based measure of downside risk. An extract of plot-level data from RALS was combined with satellite rainfall data to yield data on crop management, performance, and rainfall outcome. The chapter employed the double hurdle multinomial endogenous treatment effects model to capture the impact of adopting conservation farming on crop yield and downside risk.

This chapter, therefore, provides a discussion of overall conclusions and policy implications of the thesis. Section 5.1 discusses the key findings and section 5.2 draws the overall conclusions and discusses some policy implications of the findings. Section 5.3 attempts to highlight potential areas for further research or improvement.

5.1 Synopsis of Key Findings

The results show that there are many adaptation strategies at the disposal of smallholder farmers. Chief among these are conservation farming and irrigation. These are being promoted through a number of institutions such as the Conservation Farming Unit (CFU) and multilaterally funded projects like the Irrigation Development and Support Project (IDSP) being funded by the World Bank (WB, 2011).

On the adoption of conservation farming, the results show that farmers adopt it incrementally, starting with one component and successively adding others. The adoption of the various components is driven by different circumstances and there is a reluctance to move to full conservation farming. For instance, farmers adopt minimum tillage and crop rotation when faced with droughts. The major challenge to adopting these include the low level of access to complementing practices, such as the use of herbicides and crop diversification, or of access to specialised implements. There is an entrenched culture of maize monocropping among smallholder farmers, and this is compounded by a general lack of structured input and output markets for alternative crops.

The introduction of the multicrop FISP did ease access to inputs of other crops and the results show that this has had a significant impact on the household-level degree of crop diversification. The electronic voucher reform, although having a positive impact on crop diversification, has been hampered by the general inertia in the private markets towards providing certified inputs for alternative crops. In addition, the lack of assured markets for the outputs of crops other than maize has also worked against crop-diversification efforts. Consequently, the low level of crop diversification has also limited the extent to which farmers can practice crop rotation.

The adoption of soil cover is hampered by the culture of open grazing during the off-season and the competing use of crop residue as fodder. Crop residue is an important source of fodder that farmers cannot afford to retain as soil cover in the field. Irrigation remains restricted along surface water sources, mainly because of the high initial investment cost that many smallholder farmers cannot easily afford. Farmers are also not able to borrow in order to finance these investments, partly due to non-functional credit markets in agriculture and the general lack of the required collateral.

The results show that farmers who adopt conservation farming not only improve their yields, but their crops stand better chances of survival. Plot-level evidence shows that crops to which some components of conservation farming are applied tend to have higher yields. At the same time, these crops have a more positive skewness, implying reduced extremes on the left.

In conclusion, climate-change adaptation remains a challenge among smallholder farmers. Smallholder farmers are also failing to adopt climate-smart agricultural practices, such as conservation farming, that have proved to be especially useful in drought prone areas. Government policy reforms have been helpful but even these are not holistic enough to tackle all the bottle-necks to adaptation.

5.2 General Conclusion and Implications for Policy

The findings in this thesis have implications for the approach to agricultural policy in the future. Firstly, adaptation to climate variability has been shown to have many challenges, including the lack of appropriate skills and knowledge. At the same time, extension services have been shown to work in shaping farmers' behaviour. Therefore, there is a need to scale up extension services that provide the necessary skills for and knowledge on climate-change adaptation.

Secondly, the impact of FISP reforms in expanding crop diversification and rotation is hampered by the lack of complementing services such as market access for both certified inputs and outputs of alternative crops. Therefore, there is a need to expand reforms to other areas, such as introducing agricultural market reforms that would promote affordable access to certified inputs for other crops and to other agricultural consumables, such as agro-chemicals, which would support adaptation to climate variability. Markets for the outputs of alternative crops also need to be promoted.

Thirdly, the effectiveness of conservation farming as a climate-adaptation measure is dependent on the prevailing microclimate. Conservation farming is more effective when rainfall is low. Therefore, there should be a more targeted roll-out to the regions that would most benefit from the practice. This would help to ensure positive results, which are important for continued adoption.

5.3 Areas for Future Improvements

While the thesis has brought out a number of interesting findings, there are a number of limitations that have been noted which can provide some learning for future research. This section highlights some of the notable areas being suggested for future improvements.

First, climate adaptation among smallholder farmers is an ongoing research area with evolving circumstances. This thesis is based on the farming seasons of more than six years ago because of data limitations. Since then, the context could have changed, including rainfall distribution, technological options available and farmers' knowledge and perception of new farming practices. As more RALS waves become available, they may provide opportunities to refine our understanding of the subject with more recent data.

Second, reforms of FISP have also continued. Recent developments include the expansion of the electronic voucher input delivery system. There has also been policy pronouncements to broaden the programme to Agricultural Support Programme which will go beyond provision of inputs. Over time, the private sector may be able to expand in order to respond adequately to the demands that come with these reforms. This has the potential to alter the level of adoption and the response to FISP reforms, which may warrant further research.

Third, the scope of the thesis was to some extent limited by the availability of data. For instance, in the analysis of adaptation, only a limited number of practices were analysed, to the exclusion of other equally important and complementing practices such as use of herbicides, and the determinants of sustained adoption and decisions to dis-adopt or abandon new technologies. As noted already, Zambia is projected to become more drier and adaptation becoming increasingly more important. As more data becomes available, it may allow for the investigation of questions surrounding these issues.

Fourth, while the thesis benefited from a high resolution rainfall data, the choice and crafting of a rainfall variable was not without limitation. The use of seasonal rainfall captures the amounts of rainfall but is blind to the actual distribution, while measures that capture the distribution may fail to disentangle negative and positive deviations. As such the latter measures would treat excess rainfall as having the same effect as deficit rainfall. Therefore, there is need to devise measures that are able to capture the distribution as well as disentangle below-average deviations from above-average.

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APPENDICES

APPENDIX A

KEY INFORMANT INTERVIEWS

Key informant interviews (KIIs) were conducted with officers from DACOs offices and AEO in Chisamba and Monze districts between 17th and 24th of December, 2019. In each interview, the respondent was informed of their rights and responsibilities by reading them through the participant information sheet, whose content is shown in appendix A.1. The respondents were then asked if they were willing to participate in the study and consent was given by signing a specifically designed consent form in appendix A.2, in line with standard research ethics requirements. In addition, participants were asked to provide additional consent for the use of a voice recorder in the interview. The use of a voice recorder allowed the accurate capture of the interview information. Of the 23 respondents, 21 consented to the use of a recorder. These interviews were recorded and transcribed later. A key informant interview guide in appendix A.3 was then used to guide the interview.

A.1 Participant Information Sheet

Figure A.1 shows the participant information sheet that was used to provide key informants detailed information about the research, their rights and potential risks and benefits from participating.

Figure A.1: Participant Information Sheet

PARTICIPANT INFORMATION SHEET.

Research Title: **Assessing smallholder farmers' response to climate change**

1 Purpose of the Study

Climate change and its effects is taking centre stage especially on the agriculture sector. Though it affects the whole sector, its effects are likely more pronounced on smallholder farmers who rely on rain-fed agriculture. In response, the government and partners have been promoting the adoption of different climate smart agriculture practices including conservation farming (CF), irrigation and crop insurance. However, studies continue to show low levels of adoption of these practices, raising concerns on the level of adaptation to climate change. This study seeks to investigate smallholder farmers' response to climate change in Zambia as part of a broader study on Climate change adaptation among smallholder farmers in Zambia. The study hopes to analyse and document the policy and support framework available to help farmers adapt to climate change.

2 Description of the study and your involvement

This study has a qualitative component which involve key informant interviews with stakeholders in Zambia's agriculture sector. These include Ministry of Agriculture officials and other partners that are working around supporting smallholder farmers to adapt to climate change. You have been selected as one of the key informants based on your role in the sector. We would like to learn from you on a number of issues surrounding climate change adaptation among smallholder farmers. The interview will be conducted one-on-one and no recording devises will be used without your express permission.

3 Confidentiality

The information you provide in this study will be treated with utmost confidentiality and access to identifiable information we collect will be restricted to authorized persons within the research team only. All opinions you provide will be kept confidential and we will only report results in a way that will not directly identify you.

4 Voluntary participation and withdraw

Your participation in this study is completely voluntary. If you do not wish to participate or wish to withdraw from the study, you can do so at any time during the interview without any penalty, loss of benefits, or services you would otherwise receive. You are at liberty not to answer any questions which you may not be comfortable with. That is, if you choose to participate, you will not be obliged to respond to all questions.

5 Risks and Benefits

The study presents no known risks or dangers to you and to other members of your organisation. As described, all participation is voluntary and all participant information will remain confidential. Although we are taking down your name, no names or other identifying details will be published with the research findings. As a respondent, you will remain completely anonymous. In the same way, participation in the study does not bring any direct benefit to you or your organisation. Nonetheless, findings from the study will inform policy on smallholder farmers' response to climate change for the broader benefit of the sector and the country as a whole.

6 Contacts for Questions

This research has been **approved** by the University of Cape Town Commerce Faculty Ethics in Research Committee. For more information or if you have a complaint concerning the manner in which this research is conducted, you may contact the following people:

1. Dr. Dale Mudenda, Head - Department of Economics, University of Zambia.
   Tel. +260 21 129 0475. Email: dmudenda@unza.zm.
2. Prof. Edwin Muchapondwa, Research Supervisor, School of Economics, University of Cape Town.
   Tel: +27 21 650 5242. Email: edwin.muchapondwa@uct.ac.za.

A.2 Consent Form

Figure A.2 shows the consent form, on which key informants signed to give consent to be interviewed as well the use of the voice recorder.

Figure A.2: Participant Consent Form

PARTICIPANT CONSENT FORM.

Research Title: **Assessing smallholder farmers' response to climate change**

Introduction

This study seeks to investigate smallholder farmers' response to climate change in Zambia as part of a broader study on Climate change adaptation among smallholder farmers in Zambia. The study hopes to document and analyse the policy and support framework available to help farmers adapt to climate change. Key informant interviews are used to gather information from various stakeholders in the agriculture sector working or linked to climate change adaption. You have been selected as one of the key informants based on your role in the sector.

There are no known risks or dangers to you associated with this study. The researchers will not attempt to identify you with the responses to your questionnaire, or to name you as a participant in the study, nor will they facilitate anyone else's doing so.

Consent

I have read the **participant information sheet** provided and acknowledge that I am participating in this study of my own free will. I understand that I may refuse to participate or stop participating at any time without penalty. If I wish, I will be given a copy of this consent form.

Name (*printed*): ______________________________

Signature: ____________________ Date: ____________________

Name of Interviewer (*printed*): ____________________ Signature: __________

Use of Recorder

Please sign here if you consent to the use of a voice recorder: ____________________

A.3 Interview Guide

Figure A.3 is the abridged version of the key informant interview (KII) guide that was used in the in-depth interviews with key informants.

Figure A.3: In-depth Interview Guide

IN-DEPTH INTERVIEW GUIDE.

Research Title: **Assessing smallholder farmers' response to climate change**

Introduction

I want to get your views on a number of issues surrounding climate change, smallholder farmers and how you or other institutions are supporting farmers to adapt to climate change. I would greatly appreciate your input in this study.

May I now get your following particulars. These will be recorded separately from our discussion that follow. You **can skip any that you prefer not to provide**.

Name: ______ Age: ______ Gender: ______ Level of education: ______
Your position: ______ Years in this position: ______
Locality: ______ Years in this locality: ______

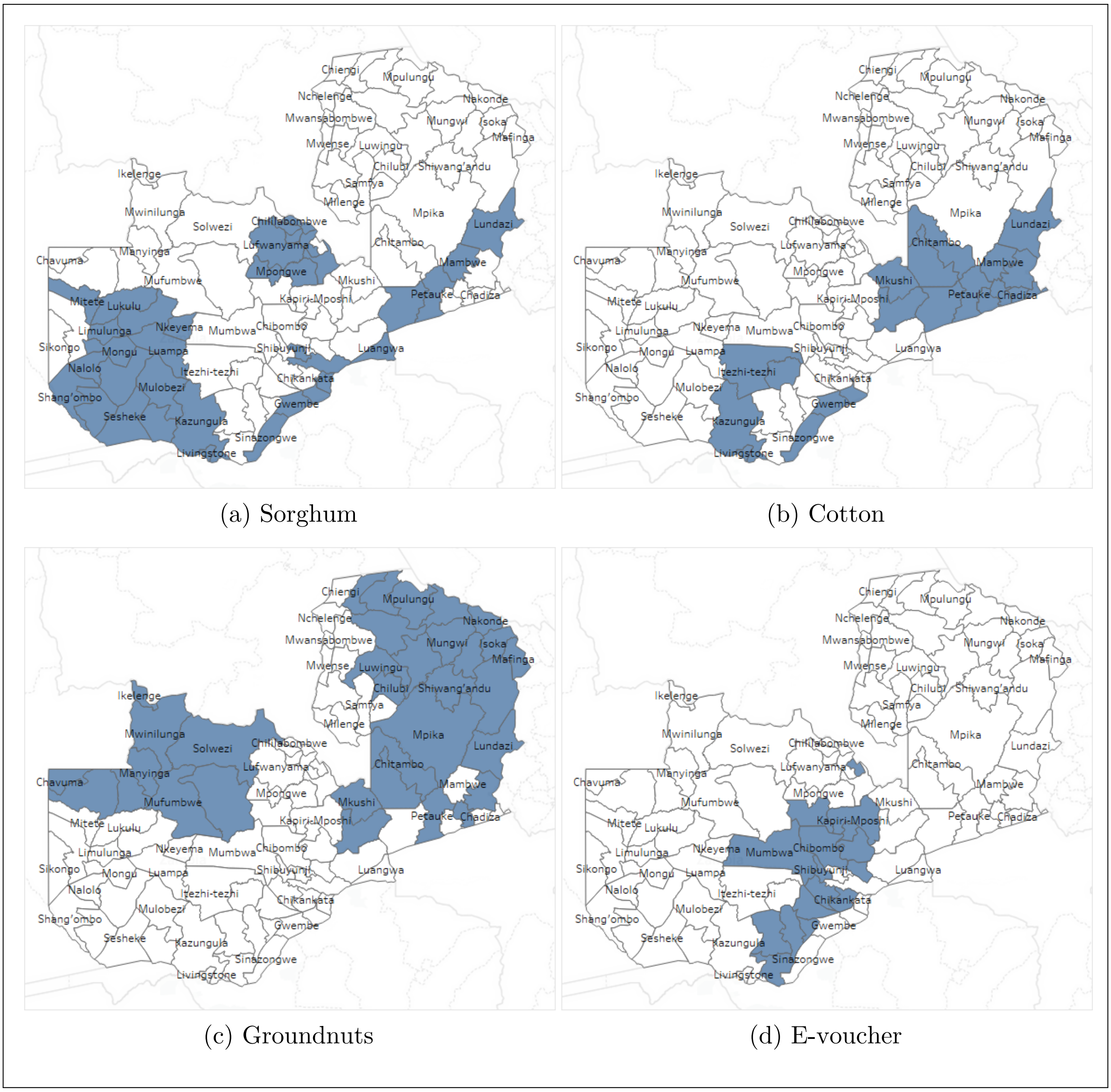
KQ 1: **Describe the weather and climate situation and how it is affecting the Agriculture sector**	
Probes	Describe the extent of change in climatic variables in this region. How do you describe the extent of effect on the smallholder farmers?
KQ 2: **What options do farmers have in responding to climate change effects?**	
Probes	What are farmers able to do in order to deal with increasingly unpredictable rains? What farming practices are working and how is the response? Are farmers adopting? What practices do you think are more appropriate for your catchment area? What are some of the challenges inhibiting full adaptation?
KQ 3: **Describe the support available to help farmers adapt to climate change.**	
Probes	What policy and strategies are in place to support smallholder farmers adapt to climate change? Describe institutions that are supporting climate change adaptation for smallholder farmers.
KQ 4: **Describe the adoption of Conservation Farming or Agriculture among smallholder farmers.**	
Probes	How effective is CF is achieving the intended objectives? To what extent is CF critical to climate change adaptation? Should focus be on CF? What are some of the barriers to adoption of CF among smallholders? How are these barriers being addressed?
KQ 5: **Describe the adoption of irrigation among smallholder farmers in your area.**	
Probes	To what extent has irrigation helped reduce the impact of climate change? What are some of the barriers to adoption of irrigation among smallholders? To what extent has water availability affected the adoption of irrigation? How are these barriers being addressed?
Any other comments.	
Probes	Are there other issues you may want to highlight around climate change adaptation among smallholder farmers

APPENDIX B

FISP REFORMS

The FISP reforms under review in this thesis are the introduction of the three crops, namely; sorghum, cotton and groundnuts and the introduction of the electronic voucher delivery system. The three crops were introduced in different but overlapping districts. Figure B.1 shows districts that received different categories of FISP inputs. In particular, sub-figure (a) show districts that received sorghum respectively while sub-figures (b) and (c) have cotton and groundnuts respectively. Figure (d) shows districts that were on the e-voucher pilot at the time.

Figure B.1: Districts receiving diversified FISP



(a) Sorghum

(b) Cotton

(c) Groundnuts

(d) E-voucher

Source: Author generated based on the FISP implementation manuals (MoA, 2012, 2013a)

APPENDIX C

ADDITIONAL TABLES

Table C.1: Full table of table 3.9: Auxiliary regression for test of attrition bias on page 98.

VARIABLES	(1) Yield_maize	(2) Yield_gnuts	(3) SID	(4) CR
attrition	1.401 (74.151)	12.218 (31.179)	0.002 (0.010)	-0.014 (0.017)
fd	-205.803*** (70.494)	30.924 (28.736)	0.077*** (0.010)	0.026 (0.016)
education	66.261*** (9.828)	14.897*** (4.146)	-0.012*** (0.001)	-0.010*** (0.002)
age	-6.355*** (1.966)	-0.410 (0.790)	0.001*** (0.000)	-0.001** (0.000)
gender (male=1)	157.690 (141.598)	2.140 (57.414)	-0.024 (0.019)	-0.022 (0.033)
household size	-16.179 (18.050)	-3.286 (7.558)	-0.003 (0.002)	0.001 (0.004)
cattle_number	11.107*** (2.180)	2.072** (0.966)	-0.002*** (0.000)	-0.001** (0.001)
land_used	-35.180*** (10.705)	-10.215** (4.309)	0.009*** (0.001)	0.018*** (0.003)
soc_net_coop	543.837*** (71.773)	35.085 (29.966)	-0.000 (0.010)	0.002 (0.017)
soc_net_wgroup	-26.261 (59.079)	15.498 (23.118)	0.016* (0.008)	0.023* (0.014)
soc_net_lsls	51.025 (121.334)	-43.098 (48.534)	-0.001 (0.017)	0.012 (0.028)
Constant	2,268*** (139)	442*** (57)	0.460*** (0.019)	0.467*** (0.032)
Observations	4,436	2,857	4,178	4,178

SEA clustered robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table C.2: Full table of table 4.4: Impact of CF adoption on climate resilience on page 134.

VARIABLES dependent variable	(1) All skewness	(2) Cereals skewness	(3) Maize skewness	(4) Category A skewness
CF category[1]				
_1	0.001 (0.088)	0.574** (0.288)	0.685** (0.326)	0.159 (0.106)
_2	0.356** (0.146)	0.268 (0.282)	0.258 (0.333)	0.048 (0.120)
_3	0.259 (0.677)	0.643** (0.251)	0.705** (0.291)	-0.258** (0.107)
_4	0.016 (0.118)	0.613** (0.240)	0.536** (0.249)	-0.045 (0.079)
_5	0.349** (0.174)	0.361** (0.154)	1.085*** (0.132)	-0.032 (0.089)
_6	0.216 (0.238)	-0.141 (0.101)	-0.131 (0.135)	0.106 (0.089)
_7	0.488*** (0.148)	0.152 (0.170)	0.086 (0.182)	-0.104 (0.093)
Plot characteristics				
fertiliser	0.001*** (0.000)	0.006*** (0.000)	0.006*** (0.000)	0.001*** (0.000)
dambo	-0.092 (0.108)	0.034 (0.140)	0.072 (0.099)	-0.110 (0.115)
floods	-0.162* (0.090)	-0.018 (0.088)	-0.059 (0.073)	-0.025 (0.083)
hectarage	-0.069*** (0.023)	0.061 (0.039)	0.116*** (0.028)	-0.204*** (0.039)
household characteristics				
age	0.001 (0.003)	-0.007** (0.003)	-0.006*** (0.002)	-0.002 (0.002)
gender	0.309 (0.254)	-0.429* (0.257)	0.037 (0.144)	0.008 (0.129)
size	-0.004 (0.029)	-0.024 (0.027)	-0.011 (0.018)	0.032* (0.018)
education	0.049** (0.020)	0.048*** (0.017)	0.026** (0.011)	-0.004 (0.012)
cattle (number)	-0.004* (0.002)	0.007 (0.006)	0.002 (0.002)	0.002 (0.005)
year_2015	-0.115 (0.110)	-0.225** (0.089)	-0.031 (0.063)	-0.187*** (0.063)
Constant	-0.524* (0.272)	-0.028 (0.205)	-0.800*** (0.162)	0.311** (0.138)
Observations	33,002	13,670	10,570	11,309

SEA clustered robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

[1] CF categories are as defined in figure 4.2 on page 125.