Econometric Analysis of Improved Maize Varieties and Sustainable Agricultural Practices (SAPs) in Eastern Zambia

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To Alice, Joel, and Jerome

&

My late parents

ABSTRACT

Maize is the principle food staple in Zambia, providing both food and income for most of the rural populace. It is estimated that over 50% of the daily caloric intake is derived from maize; with an average consumption of over 85kg per year. Because of the importance of maize, a number of improved maize varieties and sustainable crop management practices have been developed to increase its productivity. Despite these improved agricultural technologies being available for some time now, few studies have analyzed the adoption impacts of these technologies on the economic well-being of smallholder farmers in Zambia. To fill this gap in the literature, this thesis assesses the adoption and impacts of improved maize varieties and sustainable agricultural practices (SAPs) on the welfare of smallholder farmers in the Eastern province of Zambia. To accomplish this objective, we use a number of novel econometric approaches and a comprehensive household survey data from a sample of 810 rural households and 3788 plots. First, the findings suggest that the adoption of improved maize varieties is determined by a whole range of factors that include land cultivated, education of the household head and the total asset holdings of the household. Second, the results show that the adoption of improved maize varieties is associated with higher levels of income, food security, child nutritional status and lower levels of poverty. Third, the counterfactual analysis applied in this thesis shows that if non-adopters had adopted improved maize varieties, they would have realized higher levels of welfare than they currently have. Fourth, the results show that adoption of improved maize alone has greater impacts on maize yields, but given the high cost of inorganic fertilizer that limits the profitability of adoption of improved maize, higher household incomes are associated rather with the adoption of multiple SAPs.

Key words: Food security, improved maize varieties, sustainable agricultural practices, impact assessment, Zambia

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 Background

1.1.1 Agriculture and sustainable development

In recent years, most economists and development organizations have gone beyond just looking at economic development, but have proposed a more equitable and balanced type of development in sustainable development. Sustainable development is development that "meets the needs of the present without compromising the ability of future generations to meet their own needs" (Brundtland, 1987). Recognizing the importance of sustainable development, the United Nations (UN) recently formulated 17 Sustainable Development Goals (SDGs) which are meant to build upon the Millennium Development Goals and complete what MDGs did not achieve.

In Africa, achieving economic development, let alone sustainable development has been a challenge. This is evidenced by the fact that about 43% of the people in Africa live on less than \$1.9 a day, while the number of poor increased by more than 100 million (from 288 to 389 million) in 2012 (Beegle *et al*., 2016). The International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT) developed by the International Food Policy Research Institute (IFPRI) also paints a bleak picture for Africa's prospects in reducing food insecurity and malnutrition. In the years spanning from 1997 to 2020, the model projects an increase in the number of food insecure people and malnourished children (6 million) (Rosegrant *et al.*, 2001). Researchers and development practitioners (e.g. Ndulu, 2007; World Bank, 2008: Self and Grabowski, 2007) agree that agriculture, which is the main stay for many African countries for food, exports, and income is the fundamental vehicle for sustainable development and poverty reduction in the 21st century in Africa. Self and Grabowski, (2007) contend that enhancing agricultural productivity may be the most effective mechanism for improving well-being in rural areas and this in turn may promote more rapid overall economic growth. Relating to the SDGs, agriculture can therefore play a very important role in achieving sustainable development. Improving the productivity, profitability, and sustainability of smallholder farming may be the pathway of achieving especially the first two SDGs which specifically target ending all forms of poverty, hunger, achieving food security and improved nutrition. The promotion of sustainable agriculture is also mentioned in the second goal as one of the tools for achieving sustainable development. However, despite the promising prospects that agriculture offers for sustainable development, Africa's agricultural productivity, compared to other countries in the world, lags far way behind. Low productivity often results from a combination of factors, which include, low and declining soil fertility due to low levels of organic matter in the soil, limited use of improved seeds, fertilizers and other inputs, and limited access to credit for farmers (UN, 2008).

1.1.2 Agriculture and well-being in Zambia

In Zambia, agriculture is an important sector in achieving sustainable development, reducing rural poverty, improving nutrition, health, and social well-being. The sector supports the livelihoods of over 70% of the population and contributes about 13% to the national Gross Domestic Product (GDP) (Sitko *et al.,* 2011; Tembo and Sitko, 2013). Recognizing the importance of agriculture, the government of Zambia has placed agriculture as one of the priority sectors that are essential in meeting the country's long-term vision of becoming a 'prosperous middle-income nation by 2030'(MoF, 2006). The vision 2030 is a long-term plan based on policy-oriented research on key national strategic issues. In this plan, agriculture is envisioned to be efficient, competitive, and sustainable and export oriented, so that it assures food security and sufficient income by 2030.

Of the many crops grown in Zambia, maize is the principal food staple, accounting for about 60% of national calorie consumption and serving as the dietary mainstay in central, eastern and southern Zambia (Dorosh *et al.,* 2009). Over the years, Zambia has seen an increase in the production of maize mainly attributed to the increased access to maize hybrids and fertilizers through government subsidies, along with good rains (Tembo and Sitko, 2013). Zambia's estimated maize production in 2014 for instance was over 3 million metric tons (MT), with a marketable surplus from farmers of about 1.9 million MT, which represented 54% of national maize production (Chapoto *et al.,* 2015). The increased production has also been mainly due to area expansion, rather than productivity per hectare (ha). The average maize yields obtained by most smallholder farmers in Zambia of around 2 tons/ha are still very low as compared to other countries in the region (Tembo and Sitko, 2013). Figure 1.1 below shows that the average yields in Zambia have never gone beyond 3 tons/ha.

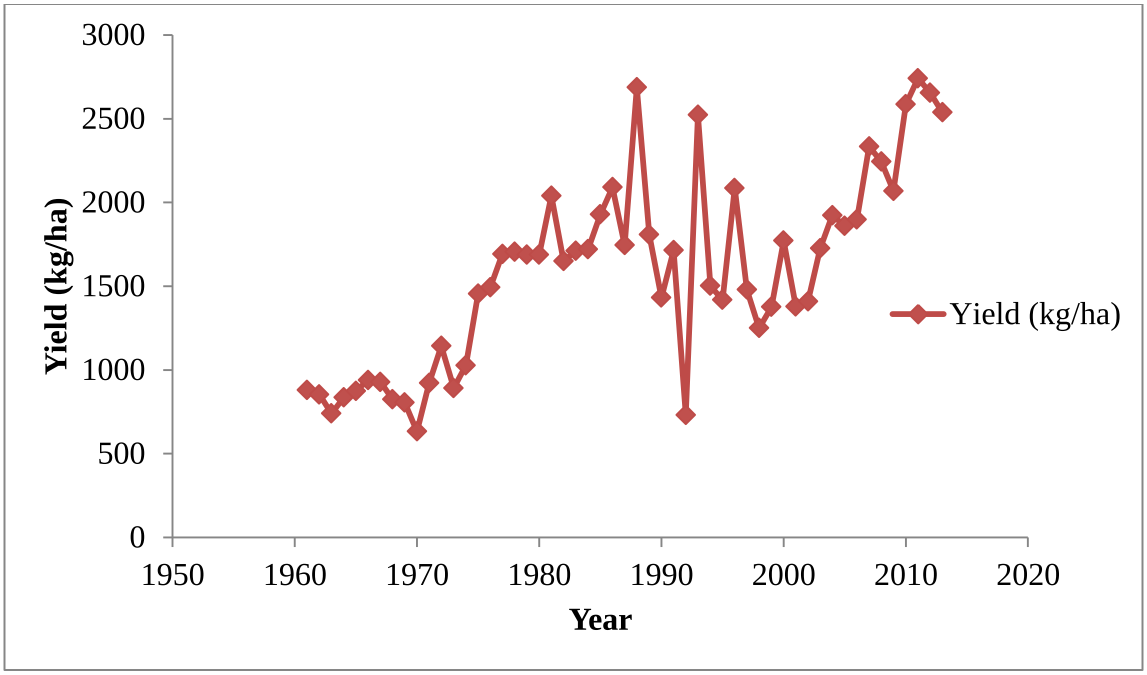

Figure 1.1: Historical development of maize yields in Zambia (1961-2013).
Source: FAOSTAT (2013).

Notwithstanding a national surplus of maize, several smallholder farmers across the country are deficit producers and net buyers of maize. This is not surprising because an estimated 80% of the rural populace, most of them smallholder farmers, are living in poverty in Zambia (Sitko *et al.*, 2011). Most of these poor farmers and women lack capital and assets to invest in improved technologies such as improved varieties and crop management practices. This translates in the low productivity observed amongst smallholder farmers and has partly contributed to the high levels of food insecurity in the country. According to Sitko *et al.* (2011), only 36% of the households have enough food to eat, while 19% seldom or never have enough to eat, categorizing them as chronically food insecure in Zambia. Other factors contributing to food insecurity at household level in Zambia include inadequate incomes and inability to purchase food and inadequate market and transport systems to take food from surplus to deficit areas within the country. Inadequate food availability is also one of the underlying causes of malnutrition in Zambia. Recent studies show that most children in rural areas are stunted (40%) while 6% and 15% are wasted and underweight respectively (CSO *et al.*, 2014). Although the percentages of stunted and underweight children have generally decreased from 53% and 15% in 2002 to the current levels, the rates are still quite high when compared to other countries in the region. This clearly shows that Zambia may not be able to attain the MDGs on malnutrition which seek to reduce the levels of stunting and underweight to 20 and 12.5% respectively by the end of 2015. Apart from food insecurity, the high disease burden and poverty are the other major causes of malnutrition in Zambia (UNDP, 2011).

1.1.3 Improved maize and crop management practices in Zambia

In an effort to sustainably increase maize production and to contribute to the reduction of problems mentioned above, a number of research organizations have been developing improved varieties as well as promoting sustainable agricultural practices. For instance the efforts of the International Wheat and Improvement Centre (CIMMYT) and International Institute of Tropical Agriculture (IITA) in collaboration with the Zambia Agricultural Institute (ZARI) have resulted into more than 50 improved maize varieties being released in Zambia (Kalinda *et al.,* 2014). Compared to the usually flinty and open pollinated local varieties, with an average yield of less than 1.5 tons/ha, improved maize varieties have been shown to increase yields by more than 50% (Howard and Mungoma, 1996; Kalinda *et al.,* 2014). As of 2012, it was estimated that about 60% of the smallholder farmers were using improved maize varieties in Zambia (Tembo and Sitko, 2013).

The increased adoption and diffusion of improved maize in Zambia from the early 1960's to date is largely due to government policies that have been skewed towards the production of maize at the expense of other crops. From independence in 1964 to date, the Zambian government has always supported the production of maize through input subsidies and maize price support. Sustained adoption of improved maize technology by Zambian smallholders, particularly those in remote areas, in the early years after Zambia's independence was also linked to the simultaneous investments in the seed industry, extension service, and marketing policies (Howard and Mungoma, 1996). Currently maize production and marketing are supported by the government through the provision of input and output subsidies, under the Farmer Input Support Program (FISP) and the Food Reserve Agency (FRA) respectively (Chapoto, *et al.,* 2015). Under the FISP programme, farmers have access to subsidized improved maize seed and fertilizers. The government also participates in maize marketing by purchasing the produce, usually at a higher price than the market price through the FRA. This has clearly helped in the promotion and adoption of improved maize varieties. Apart from government, the private sector, especially seed companies have also played an important role in the promotion of improved maize varieties. Through on-farm demonstrations and field days, farmers obtain information from them on the different improved maize varieties and are also able to compare the productivity of different varieties (Amudavi *et al*., 2009; Heiniger *et al*., 2002).

The adoption of improved maize varieties usually comes with the adoption of inorganic fertilizers and these fertilizers are not only expensive but may also have some adverse effects on the soils as well as the environment if used in abundance. The adverse effects of fertilizer application include, soil and water acidity, and disturbed nutrient balance in the soil (Ayoub, 1999). Hence achieving food security and reducing poverty, while simultaneously mitigating the degradation of essential ecosystem services is one of the major challenges faced by most sub-Saharan African countries (Teklewold *et al.,* 2013b). Sustainable agricultural practices (SAPs) provide options for increasing maize productivity with minimal adverse effects on the environment. Broadly defined, SAPs include conservation agriculture (legume crop rotations, legume intercropping, residue retention, zero tillage) improved crop varieties, application of animal and green manure, intensification and/or diversification of production (Liniger *et al.,* 2011; Kassie *et al.,* 2013; Pretty *et al.,* 2011). SAPs such as crop rotations that include legumes have been shown to increase the carbon content of soils, help fix nitrogen in soils, thereby reducing the need for inorganic fertilizer on subsequent crops, and help avoid build-up of pest populations (Pretty *et al.,* 2011; Kassam *et al.,* 2009). Similarly the use of crop residues promotes the retention and increase in organic matter, promote the soil's capacity to retain carbon, and provide water and nutrients to plant roots over sustained periods (Kassam *et al.,* 2009). Previous studies (e.g. Pretty *et al.,* 2011) have also shown that combining improved varieties with sustainable agricultural practices on average more than doubled the yields per hectare across a number of countries in Africa, including Zambia. It is because of these potential benefits that a number of donor agencies have contributed resources to research organizations in order to promote and conduct research on SAPs in Zambia.

Considering the importance of maize in Zambia, it is not surprising that recent research has focused on understanding the impacts of adopting improved maize varieties in Zambia (e.g. Mason and Smale, 2013; Smale and Mason, 2014). However, there still remains a gap in understanding the differential impact of improved maize varieties adoption on adopting and non-adopting households. Equally, even though attempts have been made to assess impacts of adopting improved maize varieties on higher level indicators of well-being (e.g. household income), research centering on understanding the adoption effects on household food security and child malnutrition is still lacking for Zambia.

As mentioned above, SAPs are becoming an important part of the farming systems in most parts of Africa. However, information relating to the factors that drive Zambian farmers to adopt these SAPs is largely missing. Similarly, despite SAPs being available for a while, the impacts of adopting these SAPs on the well-being of smallholders has not been given much attention in previous studies. Understanding how SAPs affect household welfare is very important especially when it comes to formulating policies that affect sustainability, household food security and income.

1.2 Problem statement

1.2.1 Improved agricultural technologies impact pathway

Figure 1.2 below summarizes the pathway through which the adoption of improved varieties and crop management practices are hypothesized to affect income, food security, child nutrition and poverty. It is envisaged that adoption of improved agricultural practices will naturally lead to an increase in maize yields. Increased maize yields play an important role in the generation of household income through the sale of surplus maize. More income translates into less poverty, food insecurity and child malnutrition. Increased income also helps farmers to buy other nutritious foods which may inevitably improve the food and nutritional status of children. Direct consumption of maize as a result of increased yields also ensures both food and nutritional security for the farm households. It was mentioned in section 1.1.3 that one of the basic underlying causes of malnutrition is food insecurity and poverty, hence reducing these problems also ensures improved child nutritional status.

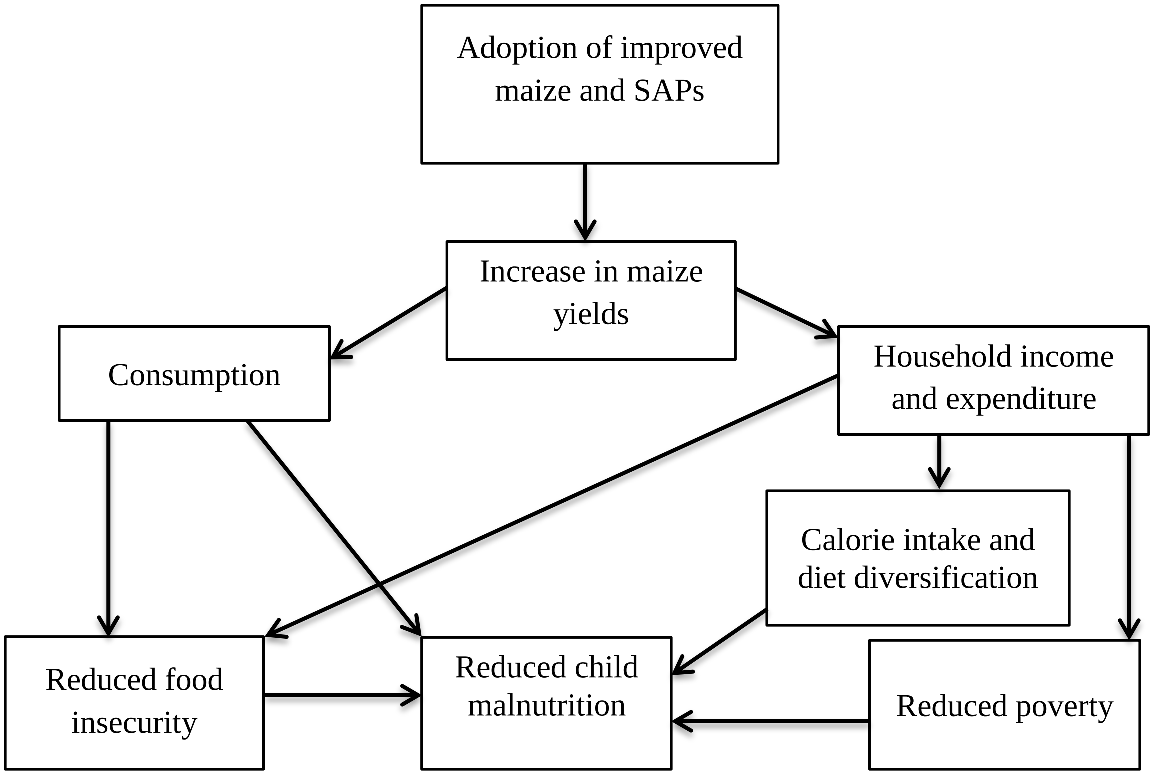

Figure 1.2: Improved agricultural technologies impact pathway.

1.2.2 Impact of improved maize varieties and SAPs on farmer's welfare

Maize is the single most important crop in smallholder farm income with about 41% of farmers' gross income attributed to it (Jayne *et al.*, 2010). The majority of the maize is produced by smallholder farmers in rural areas who make up about 80% of the entire maize produce in Zambia. The production by smallholder farmers is usually done under low soil fertility and limited adoption of high yielding varieties, inorganic fertilizers, improved technologies, extension services and output markets (Langyintuo and Mungoma, 2008; Heisey and Mwangi, 1996; Tembo and Sitko, 2013). As a result, the average maize yields per hectare produced by most small scale farmers is still very low (0.79-1.5 tons). This in essence has led to low levels of income, food security, high child malnutrition and poverty levels amongst small holder farmers. Understanding the reasons why some farmers have or have not adopted improved agricultural technologies and the possible beneficial impacts of these technologies is one of the major challenges facing researchers.

Adoption of improved agricultural technologies has been studied extensively in the recent past and papers such as those of Feder *et al.* (1985) and Feder and Umali, (1993) review the factors that may encourage or constrain adoption of agricultural technologies. Building upon these studies, most of the recent studies have gone beyond simply looking at determinants of adoption, but have extended to study the welfare impacts of these technologies (e.g. Mathenge *et al.,* 2014a; Becerril and Abdulai, 2010; Carletto *et al.,* 2011). In the case of Zambia, Mason and Smale (2013) and Smale and Mason (2014) studied the impacts of hybrid maize varieties using panel data methods on indicators of well-being. However, the downside of these studies is that they ignore the treatment effect heterogeneity. Using the intensity of seed use (kg) as one of the regressors, they assume that all adopters benefit in the same way from adoption as the impact varies according to the level of adoption. Although their approach may correct for selection bias resulting from unobservables, it may not correct for selection bias due to imbalance (both in terms of quantity as well as quality) in the covariates of adopters. To fully account for these shortcomings, the determinants and impact of improved maize adoption on indicators of well-being such as crop income, household income and poverty, should be estimated separately for adopters and non-adopters.

Since maize is the most important crop in Zambia, it implies that the crop has a major influence on both the food security and malnutrition statuses of the farm households. Improving the food security situation will involve understanding the factors that affect food security as well as the use of appropriate food security measures that relate to improved maize. Similarly, previous studies have shown that there is a dearth of information regarding the impact of agricultural technologies such as improved maize on child malnutrition (Masset *et al.,* 2011). The literature on child malnutrition shows that factors that affect child malnutrition are many (e.g. Christiaensen and Alderman, 2004; Kabubo-Mariara *et al.,* 2008; Masiye *et al.,* 2010) and isolating the effect of improved maize adoption requires innovative and careful analysis. It is interesting to investigate what factors affect child nutritional status and how improved maize affect malnutrition. This knowledge is useful in formulating targeted policies that could translate into increased adoption of improved maize varieties as well as in reducing food insecurity and malnutrition.

Sustainable Agricultural Practices (SAPS) provide additional options to resource-poor smallholder farmers to increase yields and income. SAPs may be adopted as a single technology or as a combination (package) of technologies to deal with a whole range of agricultural production constraints including low crop productivity, droughts, weeds, pests, and diseases. In addition, it has been claimed that SAPs reduce the negative impacts of climate change such as droughts by optimizing crop yields and profits while maintaining a balance between agricultural, economic and environmental benefits (Arslan *et al.,* 2013; Nyanga *et al.,* 2011). The question of whether these technologies are beneficial when they are adopted in isolation (individually) or as a combination (package) is yet to be answered in Zambia.

1.3 Objective of the thesis

The sections above highlighted the fact that agriculture is central to smallholder farmers to increase income and escape poverty. Since maize is an important crop (for both food and cash) in Zambia, it is natural to assume that adoption of improved maize varieties is essential in improving maize yields, income, household food security, child nutritional status, and poverty. Similarly, previous studies have shown that SAPs are important not only in improving the soil fertility, but also yields and incomes (e.g. Pretty *et al.,* 2011; Teklewold *et al.,* 2013b). The SAPs considered in this thesis—improved maize varieties, residue retention and maize-legume rotation—are all important in improving crop yields and income. It is therefore expected that combining all three practices will lead to the highest benefits in terms of both yields and income. Motivated by these hypothesized relationships, the general objective of the study is to assess the effects of improved agricultural technologies on the welfare of smallholder farmers in the Eastern province of Zambia.

The specific objectives of the study are to;

i. Analyse the adoption and impact of improved maize varieties on the welfare of smallholder farmers.
ii. Examine the impact of adopting improved maize varieties on household food security in eastern Zambia.
iii. Examine the determinants of long-term child malnutrition and the role of improved varieties in reducing child malnutrition.
iv. Evaluate the determinants and impact of sustainable agricultural practices on maize yields and income.

1.4 Methodological approach

1.4.1 The impact evaluation problem

In measuring the impact of a project or agricultural intervention, the main challenge that most researchers face is to determine what would have happened to the beneficiaries if the program had not existed (Khandker *et al.*, 2010). For instance, merely comparing the mean incomes of improved maize adopters and non-adopters after the intervention may lead to misleading results because the two groups may have had different characteristics even prior to the intervention. Hence the difference in the mean outcomes between the two groups can be attributed to both the impact of the program or pre-existing differences (selection bias) (Duflo *et al.*, 2007). In this case, it is difficult to decompose the overall difference into a treatment effect and a bias term because the counterfactual is not known. One way to get round this problem is by using Randomized Control Trials (RCTs). In RCTs, information on the counterfactual situation is usually provided, and as such the problem of causal inference can easily be resolved (Ali and Abdulai, 2010). In RCTs, selection bias is zero since the treatment (intervention) is randomly assigned; hence individuals assigned to the treatment and control groups differ only through their exposure to the treatment (Duflo *et al.*, 2007). In as much as RCTs produce selection bias free estimates, RCTs may not be ideal in all situations. RCTs are usually criticized because of the high cost of implementing large scale experiments (Smith and Todd, 2005; De Janvry *et al.*, 2010). Other problems border on legal, ethical and compliance issues. Legal and ethical issues may prevent researchers from persuading participation among selected treatment group members or excluding controls from alternative treatments (Heckman *et al.*, 2000).

In situations where it is not possible to implement RCTs and one has cross sectional, non-experimental data, (as the case in this thesis) alternative impact evaluation methods have to be employed to correct for selection bias. Note that selection bias can result from both observed and unobserved characteristics. In a case where it is assumed that selection bias emanates from observed characteristics, the Conditional Independence Assumption (CIA) (Lechner, 1999) or unconfoundedness (Rosenbaum and Rubin, 1983) assumption can be invoked. The assumption states that for a given set of covariates, participation is independent of potential outcomes. This allows the use of methods such as Propensity Score Matching (PSM) and propensity score reweighting (Horvitz and Thompson, 1952) to create a comparison group. In PSM, the comparison group is constructed based on a model of the probability of adopting the technology, using observed characteristics. Using this probability or propensity score, adopters are then matched with non-adopters. Propensity reweighting on the other hand use weighted averages of the observed outcome variable to estimate means of the potential outcomes. Each weight is the inverse of the estimated propensity score that an individual receives a treatment level (StataCorp, 2015). Doubly robust estimators such as the Inverse Probability Weighted Regression Adjustment (IPWRA) use propensity score reweighting to construct a comparison group. The drawback with methods that use the CIA is that construction of the comparison group is based on observed characteristics. It is possible that unobserved characteristics can motivate farmers to adopt a particular technology and in such a case, biased estimates may be obtained if these factors are not accounted for. The models based on the unconfoundedness assumption do not control for endogeneity i.e. a situation where an independent variable included in the model is correlated with unobservables relegated to the error term. In response to these problems, several Instrumental Variable (IV) based methods have been proposed.

The IV approach relies on finding a suitable instrumental variable that is correlated with technology adoption but not with unobserved characteristics that affect research outcomes such as higher yields, lower input costs, or profits (Norton, 2015). For instance, a variable would qualify as an instrument if it is correlated with the decision to adopt improved maize varieties and not food security. The main problem with this approach is finding reliable and valid instruments, which is usually difficult. Moreover, most IV approaches only identify the average treatment effect, and this might not be interesting (Norton, 2015), especially for policy implications. A question that must be asked is whether technology adoption should have an average impact over the entire sample of farmers, by way of an intercept shift in the production function, or it should be assumed to raise the productivity by way of slope shifts in the income or expenditure function (Alene and Manyong, 2007). Most IV approaches assume an intercept shift and hence estimate average impact. If the assumption is that individual covariates have a differential impact on the welfare outcomes, then separate equations for adopters and non-adopters should be estimated. This can be achieved in the Endogenous Switching Regression (ESR) model framework which accounts both for sample selection and endogeneity (Alene and Manyong, 2007). The model consists of a selection or treatment equation, which models the adoption decisions (e.g. adoption of improved maize) and two separate outcome equations (e.g. food security) for adopters and non-adopters. The model also uses an exclusion restriction rule (or IVs) for identification. It requires that at least one variable that is in the adoption equation is not in the outcome equations. These IV based approaches can even be extended to handle multivalued or multiple treatments as in the case of a multinomial treatment effects model (Deb and Trivedi, 2006b) and the multinomial endogenous switching model (Di Falco and Veronesi, 2013). In the multiple treatment case, the adoption decisions are modelled in a multinomial framework whereas the outcome equations are modeled using OLS. The same principle applies as in the ESR where the exclusion rule applies for more robust model identification.

The discussion above has shown that no single method of impact evaluation method solves the impact evaluation problem without encountering other problems. It is for this reason that a combination of methods are used to account for selection bias and endogeneity in this thesis. The methods based on the CIA are mainly used a robustness check for the IV approaches. The subsequent section gives details of how and where each individual approach was applied.

1.4.2 Methods in the analysis of adoption and impact of improved maize and SAPS

In meeting the above objectives, theories of agricultural technology adoption and impacts are employed. It is generally assumed that decisions of a farmer in a given period are derived from the maximization of expected utility (net benefits) subject to the availability of land, credit, and other constraints (Feder *et al.,* 1985). Therefore a farmer will choose or adopt an improved agricultural technology if the net benefits of using the technology are higher than benefits from other technologies. As described in section 1.2 the impact pathway that is assumed is that the improved agricultural technologies will first lead to an increase in yields, before an improvement in the higher level welfare indicators such as crop income, household income, food security, malnutrition and poverty materializes. Household and plot level data from the Eastern province of Zambia are used in meeting all the above objectives.

To meet the first objective, determinants of improved maize adoption are analyzed and the impacts of these varieties on household welfare (crop income, total household expenditure and poverty), are examined. A maize adoption dummy is used to indicate which farmers adopted improved maize (treatment variable) in the period prior to the survey. In most adoption and impact studies that use cross-sectional data, the main problem that is usually encountered is the issue of selection bias and endogeneity. This is because technology adoption may be voluntary or new technologies are targeted to a given cluster of farmers (Alene and Manyong, 2007). Farmers may self-select into the adoption or non-adoption categories depending on their innate abilities such as management ability. Not accounting for this may under- or overstate the true impact of a technology. To fully account for this, the Endogenous Switching Regression (ESR) model (Lee, 1982) is used. The ESR allows the grouping of farmers into adopters and non-adopters and therefore enables one to account for the differential responses of the two groups (Abdulai and Huffman, 2014; Alene and Manyong, 2007). Propensity Score Matching (PSM) is also used as a robustness check.

To analye the impact of improved maize varieties on food security (second objective); it is assumed that farm households make their adoption decisions following the theory of utility maximization. Following the adoption literature (e.g. Feder *et al.,* 1985), variables were selected that are hypothesized to affect adoption of improved maize varieties and food security. The food security variables used are food expenditure and self-reported food security measures. In measuring the effects of improved maize varieties on food security, misspecification of either the treatment (adoption) equation or the outcome equation was controlled by using the doubly robust inverse probability weighted regression adjustment method. In this objective, the Propensity Score Matching (PSM) approach is used as a robustness check.

The third objective requires looking at the determinants of long-term child nutritional status and the role improved maize varieties play in reducing child malnutrition. The interest is to estimate the determinants of child malnutrition and the differential impact of adoption on child nutritional status i.e. between children from adopting and non-adopting households. The selection of variables hypothesized to affect nutrition was done in the spirit of other studies such as those of Becker (1981), Christiaensen and Alderman (2004), Kabubo-Mariara *et al.* (2008) and Asenso-Okyere *et al.* (1997). The nutritional status of children was measured in terms of the anthropometric z–scores, height for age (HAZ). The construction of these anthropometric indicators was based on comparisons with a U.S. National Centre for Health Statistics (NCHS) reference group, as recommended by the World Health Organization (WHO). A child with HAZ of less than -2 standard deviations (SD) of the NCHS reference standards was considered to be stunted which is associated with factors such as chronic malnutrition, especially protein-energy malnutrition, and sustained and frequent illness. Since this objective focuses at long-term child nutritional status, a dummy to indicate stunting as the outcome of interest was used. The treatment variable that was used in this objective was an improved maize adoption dummy, which equalled one if the household planted improved maize at least three years before the survey was conducted and zero otherwise. This treatment variable was so defined because stunting is a long term measure of child malnutrition hence using a treatment variable that only captures a season may not reveal the real relation between improved maize and child malnutrition. The Endogenous Switching Probit (ESP) (Aakvik *et al.,* 2000; Lokshin and Glinskaya, 2009) was used to analyse both the determinants of child malnutrition and the impact of improved maize on child nutiriton. As robustness check, treatment effects were also estimated using the PSM approach.

In meeting the fourth objective, both household and plot level data were used. The combination of plot and household level data allows one to build a panel which in turn helps to control for selection and endogeneity bias that may arise due to correlation of unobserved heterogeneity and observed explanatory variables. The inclusion of plot level data also helps in controlling for plot quality characteristics. In meeting this objective, determinants of individual as well as combinations of SAPs were analyzed, i.e. (1) no adoption; (2) maize-legume rotation only; (3) improved maize varieties only; (4) residue retention only; (5) maize-legume rotation and improved maize; (6) maize-legume rotation and residue retention; (7) improved maize and residue retention; and (8) maize-legume rotation, improved maize, and residue retention. Similar to the objectives above, it was postulated that a farmer will choose a SAPs combination that maximizes utility subject to land and other constraints. The productivity and income gains associated with the adoption of each individual or combination of practices was also examined. It is important to note that the adoption of these practices may be endogenous to the outcome variables; hence without correcting for this, biased estimates may be obtained. To account for both the interdependence of the SAPs and endogeneity, a multinomial endogenous treatment effects model proposed by Deb and Trivedi (2006b) was used.

1.5 Outline of the thesis

This thesis is organized in seven chapters. In Chapter 2, I give an overview of the study area, including the rainfall pattern, socio-economic activities and the data used in the subsequent chapters. Chapter 3 to 5 explicitly looks at improved maize adoption and the associated impacts on several measures of household welfare in the Eastern province of Zambia. Chapter 3 is a collaborative work with Makaiko Khonje, Arega Alene and Menale Kassie and it is published in the *World Development Journal*. In this chapter, we analyse the determinants and impact of improved maize varieties on selected welfare indicators. We find that improved maize adoption increases yields, income and reduces poverty. Chapter 4 is based on joint work with Cornelis Gardebroek, Arega Alene and Elias Kuntashula. In this chapter, we ask the question of whether improved maize adoption has an effect on household food security. To answer this question, we use objective and subjective measures of food security as our outcome variables. Our results show that improved maize adoption leads to an increase in food security levels for households that adopted improved maize varieties. Specifically, the results show that the highest impacts were observed when objective measures of food security were used. In chapter 5, we analyse the determinants of child nutritional status and revisit the question of whether improved maize adoption has an impact on indicators of household well-being, but this time, child malnutrition is used as the indicator of well-being. The chapter was published in the *Journal of Food Security* and it is a joint work with Cornelis Gardebroek, Makaiko Khonje, Arega Alene, Munyaradzi Mutenje and Menale Kassie. We find that several factors determine child nutritional status including education and sanitary conditions. We also find that improved maize varieties are crucial in improving child nutritional status.

In chapter 6, together with Arega Alene, Cornelis Gardebroek, Menale Kassie and Gelson Tembo, we investigate the impact of adopting multiple SAPs on maize yields and household income. In this chapter, we compare whether adopting multiple SAPs as a package leads to higher benefits than those adopted in isolation. We find that adopting improved maize only resulted in the highest yields, but the highest income was observed when SAPs were adopted in combination. This chapter was published in the *Journal of Agricultural Economics*. In chapter 7, I discuss the main findings of this thesis, including a critical review of the findings, limitations of the study and offer recommendations for future research.

CHAPTER 2

THE STUDY AREA AND DATA USED

2.1 Introduction

This chapter gives an overview of the characteristics of the agro-ecological zones in Zambia, with a specific focus on the zone in which the study area is. Section 2.2 highlights the characteristics of the study area. Section 2.3 describes the data as well as the sampling procedure that was used, study sites and the number of households that were surveyed.

2.2 Characteristics of the study area

Zambia is divided into three agro-ecological zones denoted as regions I, II, and III. Differences in agro-climatic conditions in these regions, in addition to the differences in transport infrastructure and market access, influence farmers' cropping choices and give rise to differing food production patterns (Jayne *et al.,* 2008). Region I is a low-rainfall area receiving annual rainfall of about 800mm per year. It covers the southern part of the Southern and Western provinces and is one of Zambia's hottest, driest and poorest regions, where soils are sandy and fertility is poor (Siegel, 2008). Most of the crops grown in this area are early maturing varieties. On the other hand, region III covers about 46% of Zambia's land and receives more than 1000mm of rainfall annually, more than any other region in Zambia. Most of the soils are leached because of the high rainfall.

The study area lies in region II (figure 2.1), which is a medium-rainfall area that covers the Central, Lusaka, Southern and Eastern provinces and accounts for 42% of Zambia's land (Siegel, 2008). Region II has the highest agricultural potential due to the relatively good soils and rainfall and is the most populous, with over 4 million inhabitants (Jain, 2006; Siegel, 2008). The area receives rainfall in the range of 800mm-1000mm which is ideal for most crops in Zambia, including cassava, maize, groundnuts, millet, sorghum, beans and sweet potatoes. The study sites are mainly concentrated in three districts, namely Chipata, Katete and Lundazi. Chipata has the largest population with approximately 437 thousand people, followed by Lundazi with 308 thousand, while Katete is fourth with 235 thousand people (Tembo and Sitko, 2013). Of the three districts Chipata is most urbanized with about 25% of the people living in urban areas.

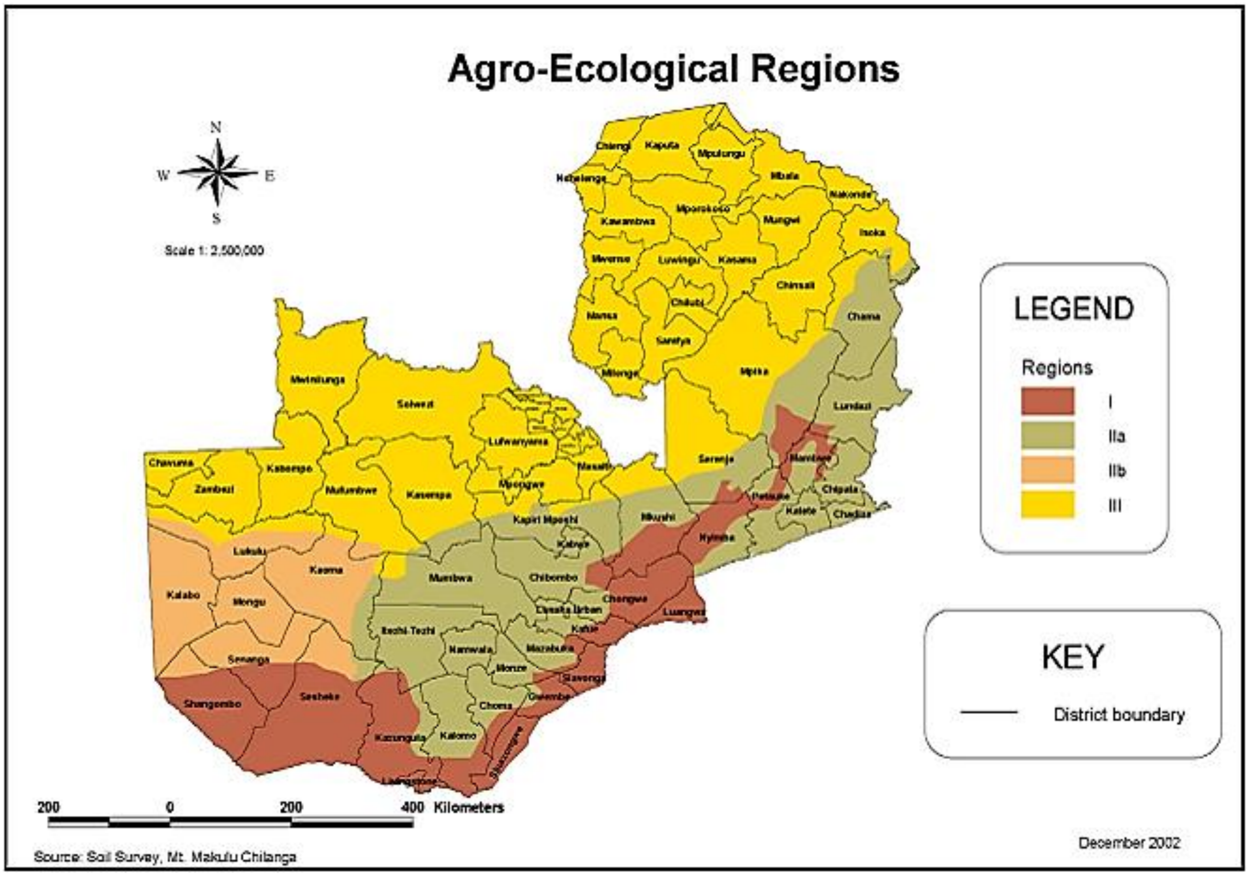

Figure 2.1: Agro-ecological zones
Source: Soil survey, Mt Makulu Chilanga (2002).

The main economic activity in the Eastern province is agriculture with maize being the most important and commonly grown crop with over 90% of the households growing it (figure 2.2). Most of the improved maize varieties grown in this area are early to medium maturing varieties, which are specifically bred for this region.

The Eastern province was selected as the study site because it is a region that has received a lot of assistance from a number of NGOs, donor organizations and the government. It also has a relatively high adoption of improved agricultural technologies including improved maize and SAPs such as conservation agriculture and is also a major producer of the main crops in Zambia. For instance in the 2011/2012 season, the province produced 570 thousand tons of maize, making it the second largest producer of maize out of 9 provinces in Zambia with 21%. Similarly, it was also the largest producer of groundnuts and soybean in Zambia during the same period with 30 thousand (28%) and 5 thousand (40%) metric tons respectively (Tembo and Stiko, 2013). According to the 2010 Census of Population, the Eastern province population is about 1.5 million people, which is about 12% of the total population in Zambia, with about 87% living in rural areas. Compared to other provinces, the province is ranked third in terms of population after Lusaka and the Copperbelt provinces. With this population, there is a great potential for commercialization of crops (e.g. maize, legumes and other high-priority staple food crops).

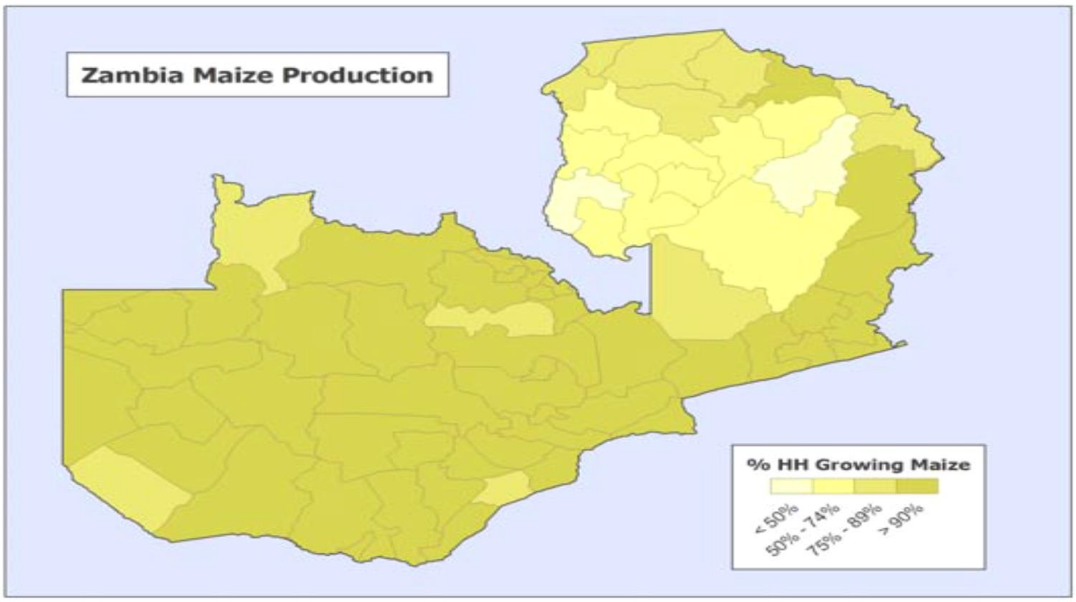

Figure 2.2: Percentage of households growing maize.
Source: Haggblade and Nielson (2007).

2.3 Description of the sampling procedure and data

The data set used in all the chapters comes from a household survey that was conducted in the 2011/2012 season. This section briefly explains the sampling procedure as well as the survey sites. Basic statistics and definitions are given in the individual chapters were the data are used.

The data used in this thesis come from a survey of 810 sample households and 3788 farming plots conducted in January and February 2012 in eastern Zambia. This was a survey conducted by IITA and CIMMYT, in collaboration with the ZARI for the project entitled Sustainable Intensification of Maize-Legume Systems for the Eastern Province of Zambia (SIMLEZA). The primary data collection was done in two stages. Initially, a reconnaissance survey was done to have a broader understanding of maize-legume and livestock production systems in the three districts of Chipata, Katete and Lundazi. Discussions were held with various stakeholders including farmers, community leaders and extension staff working with the farmers during the reconnaissance survey. Findings from this survey were used to refine the survey instruments (questionnaires) and sampling methods. The sampling frame in each district was a farmer register supplied by the district agricultural coordinator's office under the Ministry of Agriculture and Livestock (MAL).

A survey questionnaire was then prepared and administered by trained enumerators who collected data from households through personal interviews. The survey was conducted in the same SIMLEZA project districts in eastern Zambia—Chipata, Katete, and Lundazi—which were targeted by the project as the major maize and legume growing areas. In the first stage, each district was stratified into agricultural blocks (eight in Chipata, five in Katete and five in Lundazi) as primary sampling units (table 2.1).

Table 2.1: Distribution of sample households by block and district

	District			
Block	Chipata	Katete	Lundazi	Total
Central	62	42	106	210
Chanje	34	0	0	34
Chankhedze	37	0	0	37
Chiparamba	39	0	0	39
Chitandika	39	0	0	39
Eastern	45	18	0	63
Emusa	0	0	58	58
Lumezi	0	0	55	55
Lundazi central	0	0	11	11
Mwase	0	0	41	41
Northern	0	38	0	38
Southern	38	40	0	78
Valley	0	0	25	25
Western	40	42	0	82
Total	**334**	**180**	**296**	**810**

Source: Survey data (2012).

In the second stage, 40 agricultural camps were randomly selected, with the camps allocated proportionally to the selected blocks and the camps selected with probability of selection proportional to size. Note that a camp is a catchment area made up of 8 different zones comprising of villages, and is headed by an agricultural camp extension officer. Overall, 17 camps were selected in Chipata, 9 in Katete, and 14 in Lundazi. Table 2.2 shows the distribution of the sample households disaggregated by districts blocks, camps and gender.

Table 2.2: Distribution of sample household heads by district, block, camp and gender

District	Number of blocks	Number of camps	Female-headed households	Male-headed households	All
Chipata	8	17	129	205	334
Katete	5	9	63	117	180
Lundazi	5	14	98	198	296
All	18	40	290	520	810

Source: Survey data (2012).

Data was collected on the awareness as well as the adoption of various maize and legume varieties and SAPs. Farm households were asked whether they were aware of improved maize varieties, where they got the information about the variety, which year they first planted, number of seasons they have planted the variety, the amount and source of seed they planted. A good number of households were aware of the existence of improved maize varieties in the study districts and about 64% adopted these varieties. The most commonly known and adopted maize varieties in Chipata district were Pan 53 (33%) and SC 513 (12%) while in Katete district, these included DKC 8033, DKC 8053, MRI 624, MRI 634, and Pan 53. Lundazi, had Pan 53, Pan 67, MRI 624, and MRI 634 in this category. Data on improved maize adoption are used in chapters 3 through 6.

Plot level data was also collected which included the size of the plot in acres, distance of the plot from the homestead (in minutes walking), soil depth, soil fertility, soil color, slope of the land and tenure status of plots and slope. Data on the type of SAPs practiced on each plot was also collected. These include crop rotation, residue retention or mulching, percentage of intercropping, soil and water conservation, minimum tillage and improved seeds. On average, crop rotation was practiced on 11% of the plots, minimum tillage on 10%, residue retention on 13%, and intercropping on 10% of the plots. The plot level data is used in chapter 6. Figure 2.3 below shows the sites where the survey was conducted.

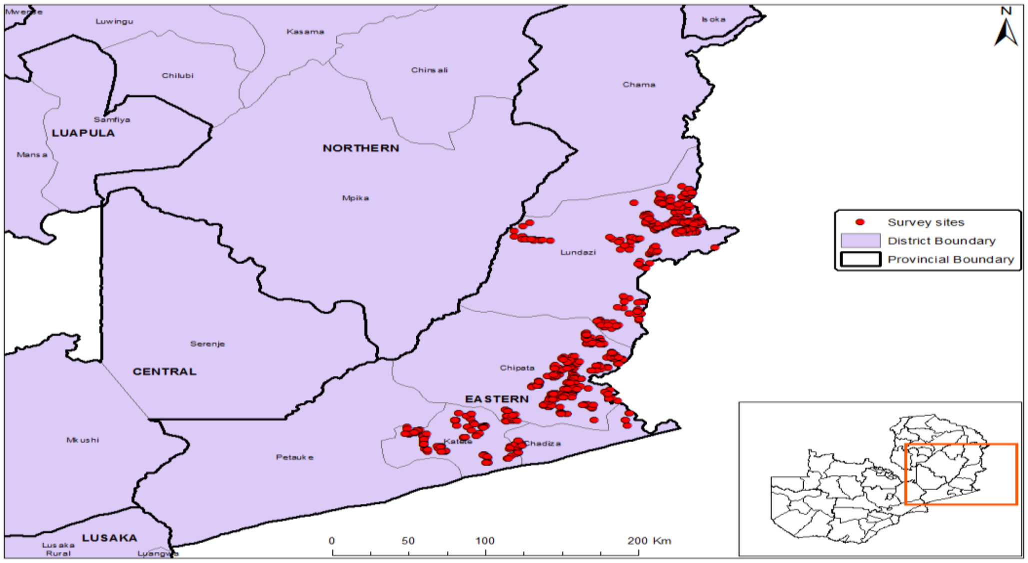

Figure 2.3: SIMLEZA survey sites.
Source: Survey data (2012).

The survey also included collection of data on maize yield, crop income, household income and expenditure, food security, and child malnutrition. Maize yield constituted the total kilograms of maize harvested on the farm in the 2011/2012 growing season. Crop income is the gross value of crop production from all the crops grown by a household, while household income includes income from crops, livestock and livestock products, and off-farm income (e.g. salaries, remittances, farm labour wage income, pension income and income from business). Similarly, expenditure includes all the expenses (food and non-food expenditure) that were incurred by a household in the survey year (e.g. expenses on staple foods, meat and other products, fats, oils, transportation costs, clothing, soap, etc.).

Information on the self-reported household food security status in the past 12 months was also collected during the survey. Based on all food sources, including own production, food purchases, food aid from different sources and food hunted from forest and lakes, etc., the respondents assessed their own food security. Respondents categorized themselves into food surplus, breakeven (no food shortage but no surplus), transitory food insecure (occasional food shortage) and chronic food insecure (shortage throughout the year). This information is used in chapter 4.

Child malnutrition is increasingly becoming an important measure of household well-being (Setboonsarng, 2005). During the survey, data on children under the age of five was collected such as age, sex, weight and height. A standard scale was used to measure the weight, while a measuring ruler was used to measure the horizontal height of the children. Using this data, anthropometric z-scores were calculated such as the height for age (HAZ) which is a long term measure of child malnutrition.

CHAPTER 3

ANALYSIS OF ADOPTION AND IMPACTS OF IMPROVED MAIZE VARIETIES IN EASTERN ZAMBIA[1]

Abstract

This chapter analyzes the adoption and welfare impacts of improved maize varieties in eastern Zambia using data obtained from a sample of over 800 farm households. Using both propensity score matching and endogenous switching regression models, the chapter shows that adoption of improved maize leads to significant gains in crop incomes, consumption expenditure, and food security. Results further show that improved maize varieties have significant poverty-reducing impacts in eastern Zambia. The chapter concludes with implications for policies to promote adoption and impacts of modern varieties in Zambia.

Key words: adoption, Africa, endogenous switching regression, propensity score matching, welfare, Zambia.

[1]Published as: Khonje, M., Manda, J., Alene, A.D., Kassie, M. (2015). Analysis of adoption and impacts of improved maize varieties in eastern Zambia. *World Development, 66, 695–706*.

3.1 Introduction

In Zambia, agriculture is vital for attaining the development goals of alleviating poverty and improving food security. Stimulating agricultural growth, and thus reducing poverty and improving food security, primarily depends on the adoption of improved agricultural technologies, including improved maize varieties.

Maize is the main staple food crop grown in Zambia and is a vital crop for food security. It is estimated that over 55% of the daily caloric intake is derived from maize, with an average consumption of about 85–140 kg per year (Sitko *et al.*, 2011). Research investment by national and international research institutions has led to the development and diffusion of improved maize varieties, and this represents a major scientific and policy achievement in African agriculture (Smale and Mason, 2014). By 2006, the adoption rate of improved maize varieties was estimated to be 37% (Smale and Mason, 2013). By 2010, 203 maize varieties had been released to farmers, over 100 of which were subsequently grown by farmers in the 2010–11 growing season (De Groote *et al.,* 2012). However, efforts aimed at enhancing the impact of maize technologies on smallholder agricultural productivity and incomes require understanding and identifying the constraints and incentives which influence the adoption of improved maize varieties.

There is limited empirical evidence on the impacts of modern technologies such as improved maize varieties in Africa. Several studies on the impacts of improved varieties (e.g. Amare *et al.,* 2012; Becerril and Abdulai, 2010; Carletto *et al.,* 2011; Crost *et al.,* 2007; Hossain *et al.,* 2006; Kassie *et al.,* 2011; Maredia and Raitzer, 2010; Mendola, 2007; Mathenge *et al.,* 2014a) have assumed that the characteristics and resources of adopters and non-adopters have the same impact on outcome variables (i.e., homogenous returns to their characteristics and resources). Many of these studies have looked at crops such as maize, groundnuts, and pigeon peas (Asfaw *et al.,* 2012; Crost *et al.,* 2007; Kassie *et al.,* 2011).

Most previous studies used single econometric models of adoption and impact. In East Africa, a recent analysis of the impact of the adoption of hybrid seed on Kenyan smallholders (Mathenge *et al.,* 2014a), builds on in-depth adoption research conducted by Suri (2011), and finds that the influence of hybrid seed on income and assets is favorable for smallholder maize growers. In Zambia, Smale and Mason (2013, 2014) applied panel data regression methods to assess the impact of the adoption of hybrid maize on the income and equality status of maize-growing smallholder farmers, using panel data for the 2002–03 and 2006–07 growing seasons. They found that growing hybrids increased gross nominal income of smallholder maize growers by an average of 29%. However, like many other studies, Smale and Mason (2013, 2014) used a regression approach that assumes that the characteristics of adopters and non-adopters have the same impact on outcome variables.

This chapter attempts to address this gap in the existing knowledge by providing a micro perspective on the adoption of maize technology and its impact on household welfare, using an endogenous switching regression (ESR) technique. The ESR results are also compared with the results based on the most commonly used propensity score matching (PSM) technique. Overall, the chapter aims to provide empirical evidence on the adoption and impact of improved maize varieties on crop income, consumption expenditure, poverty, and food security in eastern Zambia. This will help us to estimate the true welfare effects of technology adoption by controlling for selection biases on production and adoption decisions.

The rest of the chapter is organized as follows: the next section discusses survey design and data collection in three districts in eastern Zambia; the conceptual framework and estimation technique are presented in the Section 3.3; Section 3.4 presents and discusses the empirical results; Section 3.5 draws conclusions and implications.

3.2 Survey design and data collection

The data used in this chapter come from a survey of 810 sample households conducted in January and February 2012 in eastern Zambia. This was a baseline survey conducted by the International Institute of Tropical Agriculture (IITA) and the International Maize and Wheat Improvement Center (CIMMYT) in collaboration with the Zambia Agricultural Research Institute (ZARI) for the project entitled Sustainable Intensification of Maize-Legume Systems for the Eastern Province of Zambia (SIMLEZA). A survey questionnaire was prepared and administered by trained enumerators who collected data from households through personal interviews. The survey was conducted in the same SIMLEZA project districts in eastern Zambia—Chipata, Katete, and Lundazi—which were targeted by the project as the major maize and legume growing areas. In the first stage, each district was stratified into agricultural blocks (eight in Chipata, five in Katete and five in Lundazi) as primary sampling units. In the second stage, 40 agricultural camps were randomly selected, with the camps allocated proportionally to the selected blocks, and the camps selected with probability of selection proportional to size. Overall, 17 camps were selected in Chipata, 9 in Katete, and 14 in Lundazi. The distribution of the sample households by district and gender is presented in table 3.1.

Table 3.1: The distribution of the sample households by district and gender

District	Number of blocks	Number of camps	Number of households		
			Gender of household head		All
			Female-headed	Male-headed	
Chipata	8	17	129	205	334
Katete	5	9	63	117	180
Lundazi	5	14	98	198	296
All	18	40	290	520	810

A total sample of 810 households was selected randomly from the three districts with the number of households from each selected camp being proportional to the size of the camp. The survey collected valuable information on several issues at household level. Data were collected on the farmers' patterns of resource use, production practices, technology choices and preferences, constraints to market participation, improvements to maize-legume systems, socioeconomic profiles, input markets, access to services, and markets for maize and other farm outputs.

3.3 Conceptual framework and estimation technique

3.3.1 Technology adoption decision and household welfare

Following Becerril and Abdulai (2010) and Crost *et al.* (2007), the decision to adopt a technology is modeled in a random utility framework. Let P^* denote the difference between the utility from adoption (U_{iA}) and the utility from non-adoption (U_{iN}) of improved maize varieties, such that a household i will choose to adopt the technology if $P^*=U_{iA} - U_{iN}>0$. The fact is that the two utilities are unobservable; they can be expressed as a function of observable components in the latent variable model below:

$$P_i^* = Z_i\alpha + \varepsilon_i \quad \text{with } P_i=\begin{cases}1 & if\ P_i^*>0\\ 0 & otherwise\end{cases} \qquad (1)$$

where P is a binary 0 or 1 dummy variable for the use of the new technology; P = 1 if the technology is adopted and P = 0 otherwise. α is a vector of parameters to be estimated; Z is a vector that represents household- and farm-level characteristics; and ε_i is the random error term.

The adoption of new agricultural technologies can help to increase productivity, farm incomes, and food security, and help to reduce poverty levels, thus improving household welfare. Assuming that the variable of interest here—crop income, consumption expenditure, poverty status, and food security—is a linear function of a dummy variable for improved maize variety use, along with a vector of other explanatory variables (X) leads to the following equation:

$$Y_h = \gamma X_h + \delta P_h + \mu_h \quad (2)$$

where Y_h represents the outcome variables, P is an indicator variable for adoption as defined above, γ and δ are vectors of parameters to be estimated, and μ is an error term. The impact of adoption on the outcome variable is measured by the estimations of the parameter δ. However, if δ is to accurately measure the impact of adoption of improved maize varieties on outcome variables, farmers should be randomly assigned to adoption or non-adoption groups (Faltermeier and Abdulai, 2009).

3.3.2 Impact evaluation of technology adoption

Estimation of the impact of technology adoption on household welfare outcome variables based on non-experimental observations is not trivial. What we cannot observe is the outcome variable for adopters, in the case that they did not adopt. That is, we do not observe the outcome variables of households that adopt, had they not adopted (or the converse). In experimental studies, this problem is addressed by randomly assigning adoption to treatment and control status, which assures that the outcome variables observed on the control households without adoption are statistically representative of what would have occurred without adoption. However, adoption is not randomly distributed to the two groups of households (as adopters and non-adopters), but rather to the household itself deciding to adopt given the information it has, therefore adopters and non-adopters may be systematically different (Amare *et al.*, 2012). Most studies (Kalinda *et al.*, 2010; Hamazakaza *et al.*, 2013; Langyintuo and Mungoma, 2008; Mason *et al.*, 2013; Smale and Mason, 2013; Smale and Mason, 2014) have utilized single econometric models such as correlated random effects (CRE), Tobit, double hurdle, and other fixed-effect models. The disadvantage of using a single model is that the estimates are not robust enough because each model has its own limitations which cannot be individually corrected. Unlike most previous studies, this chapter uses recent (2012) data and two different econometric approaches—

endogenous switching regression (ESR) models and propensity score matching (PSM) in impact analysis for Zambia.

Endogenous switching regression

The major objective of this chapter is to explore the impacts of adopting improved maize varieties on crop income, consumption expenditure, poverty, and food security, measured by the average treatment effect on the treated (ATT). The ATT computes the average difference in outcomes of adopters with and without a technology. Most commonly used methods to calculate ATT such as PSM ignore unobservable factors that affect the adoption process, and also assumes the return (coefficient) to characteristics to be same for adopters and non-adopters, which is not the case in many recent empirical analyses (e.g. Asfaw *et al.,* 2012; Di Falco *et al.,* 2011; Teklewold *et al.,* 2013b; Shiferaw *et al.,* 2014). Modeling of the impact of adopting improved maize on the four outcome variables under the ESR framework proceeds in two stages: the first stage is the decision to adopt an improved maize variety (equation 1), and this is estimated using a probit model; in the second stage an Ordinary Least Squares (OLS) regression with selectivity correction is used to examine the relationship between the outcome variables and a set of explanatory variables conditional on the adoption decision. The two outcome regression equations, conditional on adoption can be expressed as:

Regime 1 (Adopters): $y_{1i} = x_{1i}\beta_1 + w_{1i}$ if $P = 1$ (3a)

Regime 2 (Non-adopters): $y_{2i} = x_{2i}\beta_2 + w_{2i}$ if $P = 0$ (3b)

where x_{1i} and x_{2i} are vectors of exogenous covariates; β_1 and β_2 are vectors of parameters; and w_{1i} and w_{2i} are random disturbance terms. According to Shiferaw *et al.* (2014), it is important for the *Z* variables in the adoption model to contain a selection instrument in addition to those automatically generated by the non-linearity of the selection model of adoption, for the ESR model to be identified. The selection instruments we used include the following: distance to agriculture extension office (walking minutes); market information (yes=1); information on farm technologies (yes=1); and group membership (yes=1). Following Di Falco *et al.* (2011), selection instruments were selected by performing a simple falsification test: if a variable is a valid selection instrument, it will affect the technology adoption decision but it will not affect the welfare outcome variable. Results show that the selected instruments can be considered as valid, as they are jointly statistically significant in explaining adoption decision [χ^2= 215(p = 0.000)] but are not statistically significant in explaining the outcome equation [F= 1.01(p = 0.451)][2].

The estimation of β_1 and β_2 using OLS may lead to biased estimates, because the expected values of the error terms ($w_1$and w_2) conditional on the selection criterion are non-zero (Shiferaw *et al.*, 2014). The error terms in equations (1) and (3) are assumed to have a trivariate normal distribution with mean vector zero and covariance matrix:

$$\Omega = \text{cov}\,(\varepsilon, w_1, w_2) = \begin{bmatrix} \sigma_\varepsilon^2 & \sigma_{\varepsilon 1} & \sigma_{\varepsilon 2} \\ \sigma_{\varepsilon 1} & \sigma_1^2 & . \\ \sigma_{\varepsilon 2} & . & \sigma_2^2 \end{bmatrix} \quad (4)$$

where σ_ε^2 =var (ε), σ_1^2 = var (w_1) , $\sigma_2^2 =$ var (w_2) $\sigma_{\varepsilon 1} = cov(\varepsilon, w_1)$, and $\sigma_{\varepsilon 2} = cov(\varepsilon, w_2)$. We can assume that σ_ε^2 is equal to 1 since the β coefficients in the selection model are estimable up to a scale factor. The covariance between $w_1$and w_2 is not defined since y_1 and y_2 are never observed simultaneously (Maddala, 1983). An important implication of the error structure is that because the error term of the selection equation (1) ε_i is correlated with the error terms of the welfare outcome functions (3) ($w_1$and w_2), the expected values of $w_1$and w_2 conditional on the sample selection are non-zero (Asfaw *et al.*, 2012):

$$E(w_{1i}|P=1) = \sigma_{\varepsilon 1}\frac{\phi(Z_i\alpha)}{\Phi(Z_i\alpha)} \equiv \sigma_{\varepsilon 1}\lambda_1 \quad (5)$$

$$E(w_{2i}|P=0) = \sigma_{\varepsilon 2}\frac{\phi(Z_i\alpha)}{1-\Phi(Z_i\alpha)} \equiv \sigma_{\varepsilon 2}\lambda_2 \quad (6)$$

where ϕ is the standard normal probability density function, Φ the standard normal cumulative density function, $\lambda_{1i} = \frac{\phi(Z_i\alpha)}{\Phi((Z_i\alpha)}$ and $\lambda_{2i} = \frac{\phi(Z_i\alpha)}{1-\Phi(Z_i\alpha)}$ where λ_1 and λ_2 are the inverse mills ratio calculated from the selection equation and will be included in 3a and 3b to correct for selection bias in a two-step estimation procedure i.e., ESR model. The above ESR framework can be used to estimate the average treatment effect of the treated (ATT), and of the untreated (ATU), by comparing the expected values of the outcomes of adopters and non-adopters in actual and counterfactual scenarios. Following Di Falco *et al.* (2011) and Shiferaw *et al.* (2014), we calculate the ATT and ATU as follows:

[2] Detailed results for falsification test are not presented in the chapter. But they can be provided to the individuals upon requests.

Adopters with adoption (observed in the sample)

$$E(y_{i1}|P = 1; x) = x_{i1}\beta_1 + \sigma_{\varepsilon 1}\lambda_{i1} \quad (7a)$$

Non-adopters without adoption (observed in the sample)

$$E(y_{i2}|P = 0; x) = x_{i2}\beta_2 + \sigma_{\varepsilon 2}\lambda_{i2} \quad (7b)$$

Adopters had they decided not to adopt (counterfactual)

$$E(y_{i2}|P = 1; x) = x_{i1}\beta_2 + \sigma_{\varepsilon 2}\lambda_{i1} \quad (7c)$$

Non-adopters had they decided to adopt (counterfactual)

$$E(y_{i1}|P = 0; x) = x_{i2}\beta_1 + \sigma_{\varepsilon 1}\lambda_{i2} \quad (7d)$$

The average treatment effect on the treated (ATT) is computed as the difference between (7a) and (7c);

$$ATT = (y_{i1}|P = 1; x) - (y_{i2}|P = 1; x), = x_{i1}(\beta_1 - \beta_2) + \lambda_{i1}(\sigma_{\varepsilon 1} - \sigma_{\varepsilon 2}) \quad (8)$$

The average treatment effect on the untreated (ATU) is given by the difference between (7d) and (7b);

$$ATU = (y_{i1}|P = 0; x) - (y_{i2}|P = 0; x), \quad = x_{i2}(\beta_1 - \beta_2) + \lambda_{i2}(\sigma_{\varepsilon 1} - \sigma_{\varepsilon 2}) \quad (9)$$

The expected change in the mean outcome of adopters if adopters or non-adopters had similar characteristics to non-adopters or adopters is captured by the first term on the right of equations. (8) and (9). The second term (λ) is the selection term that captures all potential effects of the difference in unobserved variables.

Propensity score matching

Since results from ESR may be sensitive to its model assumption i.e., selection of instrumental variables, we also used the PSM approach to check robustness of the estimated treatment effect results from the ESR. Following Heckman *et al.* (1997), let Y_1 be the value of welfare when the household i is subject to treatment ($P = 1$) and Y_0 the same variable when the household does not adopt an improved maize variety ($P = 0$). Then following Takahashi and Barrett (2013), the ATT can be defined as:

$$ATT = E\{Y_1 - Y_0 | P = 1\} = E(\, Y_1 | P = 1) - E(Y_0 | P = 1) \tag{10}$$

We can observe the outcome variable of adopters $E\ (Y_1 |\ P = 1)$, but we cannot observe the outcome of those adopters had they not adopted $E\ (Y_0\ |P = 1)$, and estimating the ATT using equation (10) may therefore lead to biased estimates (Takahashi and Barrett, 2013). Propensity score matching relies on an assumption of conditional independence where, conditional on the probability of adoption, given observable covariates, an outcome of interest in the absence of treatment, Y_1 and adoption status, P are statistically independent (Takahashi and Barrett, 2013). Rosenbaum and Rubin (1983) define the propensity score or probability of receiving treatment as:

$$p(X) = pr(P = 1)|X \tag{11}$$

Another important assumption of PSM is the common support condition, which requires substantial overlap in covariates between adopters and non-adopters, so that households being compared have a common probability of being both an adopter and a non-adopter, such that $0 < p(X) < 1$ (Takahashi and Barrett, 2013). If the two assumptions are met, then the PSM estimator for ATT can be specified as the mean difference of the adopters matched with non-adopters who are balanced on the propensity scores and fall within the region of common support, expressed as:

$$ATT = E(\, Y_1 | P = 1, p(X)) - E(Y_0 | P = 1, p(X)) \tag{12}$$

The PSM technique is a two-step procedure: firstly, a probability (logit or probit) model for adoption of improved maize varieties is estimated to calculate the propensity score for each observation; secondly, each adopter is matched to a non-adopter with similar propensity score values, in order to estimate the ATT (for further reading on PSM, see Abadie and Imbens, 2012). Despite the fact that PSM tries to compare the difference between the outcome variables of adopters and non-adopters with similar characteristics in terms of quantity[3], it cannot correct unobservable bias because it only controls for observed variables (to the extent that they are perfectly measured).

[3] Adopters and non-adopters can have the same average education but this does not necessarily mean education has the same return (coefficient) on outcome variable for both groups of households as the quality of education may vary across the group.

Measuring poverty

The Foster, Greer, and Thorbecke (1984) indices are commonly used to measure poverty in a population and are generally presented as:

$$R_\theta = \frac{1}{N}\sum_{i=1}^{H}\left[\frac{l-e_i}{l}\right]^\theta \quad (13)$$

where l is the agreed-upon poverty line (US$1.25/capita/day) adjusted for purchasing power parity, N is the number of people in the sample population, H is the number of poor (those with consumption expenditure per capita at or below l), e is consumption expenditure per capita for the i^{th} person, and θ is a poverty aversion (sensitivity) parameter[4]. The Foster, Greer, and Thorbecke (FGT) poverty index was computed, especially the headcount ratio, and others indices were generated in S*tata* 13 using *dasp* command, which is very powerful if one wants to decompose poverty indices by population subgroups (i.e. district and adoption category). In this chapter, we used the international poverty line of US$1.25/capita/day, which was converted to ZMK1.45 million[5] per capita per year using purchasing power parity. The consumption expenditure data was used because it gives a better poverty measurement than income (Christiaensen *et al.,* 2002).

3.4 Results and Discussion

3.4.1 Socioeconomic characteristics of the sample households

Table 3.2 presents the means of selected variables by district and adoption category (1= adopters[6] and 0 otherwise). Adoption of maize was measured by the proportion of households adopting and area share planted to improved varieties; results are presented in table 3.2. Results show that nearly all of the surveyed farmers grew maize in the 2011–12 growing season, and 64% of these maize growers were adopters. Lundazi district had the highest adoption rate (80%), while Chipata and Katete districts had lower adoption rates of 56% and 51% respectively. On the intensity of adoption (measured by area share planted to maize), it was found that 46% of the cultivated land was planted to improved maize varieties in eastern Zambia. Lundazi district had

[4] When $\theta = 0$, R_θ reduces to the headcount index or proportion of people who are poor. When θ=1, R_θ is the poverty gap index, a measure of the depth of poverty defined by the mean distance to the poverty line, where the mean is formed over the entire population with the non-poor counted as having a zero poverty gap. When θ=2, R_θ is a measure of severity of poverty and reflect the degree of inequality among the poor.

[5] Poverty measures were calculated based on poverty line of US$1.25/capita/day which was converted to ZMK1.45 million/capita/year at purchasing power exchange rate of ZMK3, 170.

[6] An adopter in this study is defined as any farmer who planted at least any of improved maize varieties.

the highest area share (63%) while Chipata and Katete districts had lower area shares planted with improved maize varieties of 38% and 32%, respectively. We used the former (binary adoption) as compared to the latter (intensity of adoption) in the empirical analysis. The results also show that farmers adopted both local and improved varieties in order to maximize advantages of preferred traits such as superior yield, taste, and resistance to diseases, and water lodging, as noted by Bellon *et al.*(2006).

The results show that adopters are also distinguishable in terms of household characteristics such as education and household size. Education is hypothesized to have a positive impact on technology adoption (Huffman, 2001). The level of education of the household head is significantly higher for adopters than non-adopters, and this makes them better able to understand the importance of adopting modern agricultural technologies. Adopters are also relatively older than non-adopters. On the dependency ratio[7], the ratios were 1.08 and 1.28 for adopters and non-adopters respectively. Adopters were supporting a fewer number of people who were either young or very old compared to non-adopters. Adopters owned more land than non-adopters. Farmers can only allocate more land to improved varieties if they have enough land, and therefore those who own more land are expected to have a comparative advantage when it comes to adopting improved maize varieties. As noted by Smale and Mason (2013), farm size has an increasingly positive effect on the probability that maize-growing households plant hybrids. The results further indicate that households in Lundazi have more land of over 4 hectares compared to those in the other districts. Adopters are also distinct in terms of asset holdings (e.g. oxen and non-oxen assets) and have more assets than non-adopters. Farmers have more assets in Lundazi district than those in Katete and Chipata districts. Smale and Mason (2014) also noted that the average value of assets for maize hybrid users was more than half as much as the value of assets of non-hybrid users in Zambia.

Adopters had more access to extension services and information about farm technologies than non-adopters. Market information is important for adopters of improved maize. Therefore institutional support services such as access to extension services[8] are important in the dissemination of new technologies and consequently affect their impact on household welfare

[7] Dependency ratio (percent of working-age population) gives an indication of how much responsibility do economically active persons have in providing needs for the dependents younger than 15 years and older than 64 years.

[8] Access to extension services was measured by number of farmers' contact with either government or non-government extension agents.

(Abdulai and Huffman, 2014). Farmers can only adopt modern technologies if they know their inherent characteristics (Adegbola and Gardebroek, 2007). Membership of a farmers group significantly affects adoption: the number of households belonging to such a group was considerably higher for adopters i.e., more adopters belonged to either formal or informal institutions that work on agriculture-related activities than non-adopters.

The adopters of improved maize were also significantly distinguishable in terms of welfare outcome indicators, measured in terms of crop income, consumption expenditure, food security, and poverty. As far as consumption expenditure was concerned, the adopters had higher consumption expenditure compared to the non-adopters. The results also indicate that adopters and farmers in Lundazi had more crop income than non-adopters and those in Katete and Chipata districts. Concerning food security, the results show that 78% of adopters were food secure, compared with 69% of non-adopters. As noted by Shiferaw *et al.* (2014), adoption of improved varieties significantly increases food security. Consistent with the greater adoption of improved maize, we expected Lundazi district to have the highest proportion of households who were food secure. On the contrary, it is Katete district which has the highest proportion of farm households who were food secure[9]. This entails that most households get food from other sources—food purchase, donation, gifts, forest and lakes and other different sources as adoption rate for improved maize varieties is lowest in the district. Higher adoption rate can lead to increased food security if most of food comes from own production as compared to other sources like food purchase or food from different sources.

Poverty in eastern Zambia is high (69%), with depth and severity indices indicating significant shortfalls in income (especially crop and livestock income) below the poverty line, and a high degree of income inequality among poor farmers. Adopters (62%) were less poor than non-adopters (82%). Smale and Mason (2014) found that the mean severity of poverty was greater among smallholder maize growers who did not plant hybrid seed (0.56 vs. 0.41). Across the districts, the poverty headcount index shows that Katete had the highest proportion of poor people, pegged at 76%, followed by Chipata (73%) and Lundazi (60%).

[9] The inconsistency between adoption rate and food security status in Katete district might be attributed to source of food in measuring food security. Food security was measured through self-assessment—we asked farmers to consider food from various sources such as own food production, food purchase, help from different sources, and food hunted from forest and lakes.

Table 3.2: Socioeconomic characteristics of the sample households by district and adoption category

Variable	District			Adoption category		All
	Chipata	Katete	Lundazi	Adopters	Non-adopters	*(N=810)*
	(N=334)	*(N=180)*	*(N=296)*	*(N=517)*	*(N=293)*	
Self-assessment food security (secure =1; insecure = 0)	0.69	0.84	0.75	0.78	0.69	0.75
Adoption of maize varieties						
Adoption status (Adopter = 1)	0.56	0.51	0.80	0.64	0.36	1.00
Intensity of adoption (% area under improved maize)	38	32	63	46	54	100
Poverty measure [a]						
Headcount index	0.73	0.76	0.60	0.62	0.82	0.69
Poverty gap index	0.41	0.42	0.30	0.30	0.49	0.37
Poverty severity index	0.26	0.27	0.18	0.18	0.34	0.23
Total household income ('000 ZMK/capita)	1094	1299	3241	2510	890	1924
Crop income ('000 ZMK/capita)	657	956	2626	1911	617	1443
Livestock income ('000 ZMK/capita)	36	-1	19	33	2	22
Non-farm income ('000 ZMK/capita)	400	344	596	566	271	459
Consumption expenditure ('000 ZMK/capita)	6868	6816	5436	7362	4513	6332
Area planted to maize (ha)	1.50	1.83	2.73	2.43	1.26	2.01
Household size (number)	7	6	7	7	6	7
Gender of the household head (Male =1)	0.61	0.65	0.67	0.64	0.64	0.64
Age of household head (years)	43	43	43	44	42	43
Education of the household head (years)	5.7	5.4	7.4	6.8	5.3	6.2
Dependency ratio (number)	1.21	1.12	1.12	1.08	1.28	1.16
Total owned land (ha)	2.64	3.04	4.37	4.08	2.46	3.36
Total rented in land (ha)	0.08	0.05	0.15	0.13	0.03	0.10
Total operated land (ha)	2.79	3.15	4.57	4.16	2.41	3.52
Value of oxen assets ('000 ZMK/capita)	61	119	117	124	49	97
Value of non-oxen assets ('000 ZMK/capita)	1074	720	1339	1435	486	1092
Own a bicycle (Yes =1)	0.75	0.86	0.81	0.82	0.76	0.80
Own ox-cart (Yes =1)	0.16	0.29	0.21	0.26	0.13	0.21
Contacts with extension agents (number)	9	16	13	14	9	12
Contacts with NGO extension agents (number)	4	4	5	5	3	4
Had marketing information (Yes =1)	0.60	0.61	0.74	0.75	0.48	0.65
Had information on improved technology (Yes =1)	0.75	0.78	0.83	0.84	0.71	0.79
Had access to credit (Yes =1)	0.76	0.86	0.71	0.75	0.78	0.76
Had access to seed (Yes =1)	0.99	1	1	0.99	1	1
Member of farmer group (Yes =1)	0.88	0.82	0.96	0.96	0.78	0.90
Distance to main market (minutes of walking time)	437.20	264.32	532.72	420.06	459.38	434.32
Distance to extension office (minutes of walking time)	68	62	65	68	61	66

[a] Poverty measures were calculated based on poverty line of US$1.25/capita/day which was converted to ZMK1.45 million/capita/year at purchasing power exchange rate of ZMK3,170. ZMK= Zambia Kwacha.

The results further show that there is an inverse relationship between poverty and farm size. Households who had a relatively smaller farm size (0.1–3.5 hectares) had a high incidence of poverty (54%) as opposed to 33% for those who had larger farms (> 3.5 hectares) (table 3.3). Land is indeed a critical productive resource for agricultural development and poverty reduction measures. Farmers who have more land are able to grow or allocate more land to a particular crop or to different crops, and consequently get a greater return from agricultural production. Sometimes farmers can even use their land as collateral to access agricultural loans—i.e. for inputs like fertilizer. Jayne *et al.* (2009) found that there is a strong relationship between size of landholding and household per capita income, especially for households owning less than 1.25 hectares of land (which applies to roughly 45% of the smallholder population in Zambia).

Table 3.3: Poverty status in eastern Zambia by education level and land ownership (% of households)

Variable	Education level		Land ownership		
	Literate	Illiterate	Near landless (<1 ha)	Small farms (1–3.5 ha)	Large farms (>3.5 ha)
Poor households	85	15	12	57	31
Non-poor households	94	6	14	46	40
All	88	12	13	54	33

Technology adoption reduces poverty and improves food security by increasing agricultural production and productivity. Table 3.4 presents farm-level economic benefits and variable costs incurred in maize production systems. The results indicate that adopters realized maize yields of 2.96 tons/hectare for improved maize varieties, representing a yield gain of 26%. Gross margin analysis was done to provide a snapshot view of net returns to adoption of improved maize varieties. The results in table 3.4 show that more variable costs were incurred to produce improved varieties as compared to local varieties. In fact, variable costs were higher by 64% for improved maize varieties. Although the costs were higher for the improved maize varieties, the net returns of ZMK3 million per hectare were comparatively high by 20%. This means that farmers found improved maize varieties to be more profitable than local maize varieties. It is worth noting, however, that the descriptive results are only indicative of the impacts of new technologies, and the empirical analysis that follows aims to provide more formal and conclusive evidence of the impacts of improved maize varieties in eastern Zambia.

Table 3.4: Comparative farm-level economic benefits from maize varieties

Variable	Variety type		Gain
	Local varieties (*N*=293)	Improved varieties (*N*=517)	(%)
Yield (tons/ha)	2.34	2.96	26
Gross value of production ('000 ZMK/ha)	2971	3745	26
Variable costs ('000 ZMK/ha)	418	687	64
Net income ('000 ZMK/ha)	2553	3058	20

Note: The exchange rate at the time of the survey was US$1= ZMK5197.

3.4.2 Empirical results

Determinants of technology adoption

The estimated parameters of the logit model of adoption of improved maize varieties are presented in table 3.5. The logit model has a McFadden pseudo R^2 of 0.20 and correctly predicts 73% and 49% of adopters and non-adopters, respectively. Overall, ten variables were found to be significant in explaining adoption of improved maize varieties. These included the following: education of the household head; household size; distance to extension office; per capita assets (non-oxen and oxen assets); access to information about improved technology; market information; group membership; and the Lundazi district dummy.

The results show that education of the household head has a positive and significant influence on adoption of improved maize varieties. This is consistent with the expectation that the probability of adoption of new agricultural technologies such as improved maize varieties increases with the level of education of the household head due to greater awareness of the availability and benefits of new agricultural technologies. Education not only facilitates adoption but also enhances productivity, especially among adopters of improved technology. Alene and Manyong (2007) found that education had a greater impact on cowpea yields among adopters of improved varieties relative to its effect on yields among non-adopters.

Results further show that access to extension services increases the likelihood of adoption of improved maize varieties. Farmers who are regularly visited by extension workers and those who attend field days or host demonstration/trials are likely to adopt modern agricultural technologies due to their increased exposure and awareness. Farmers can only adopt modern agricultural technologies if they are aware of the availability and benefits of these technologies and their inherent characteristics (Adegbola and Gardebroek, 2007). Similar results were also found for adoption of improved maize and pigeon peas in Tanzania (Amare *et al.*, 2012) and for sorghum in Ethiopia (Geberessiliese and Sanders, 2006). Increased access to institutional support services such as extension, credit, and input supply should thus be a major part of efforts aimed at promoting adoption of modern technologies.

Table 3.5: Logit estimates of the determinants of adoption of improved maize varieties in eastern Zambia

Variables	Coefficient
Age of household head	0.01 (0.01)
Head education 1–4 years	0.06 (0.09)
Head education 5–8 years	0.11 (0.04)***
Head education 9–12 years	0.06 (0.03)**
Head education >12 years	0.09 (0.06)
Household size	0.05 (0.03)*
Rented in land	0.55 (0.38)
Contacts with extension agents	0.00 (0.00)
Contacts with NGO's extension agents	0.00 (0.00)
Distance to main market	-0.00 (0.00)
Distance to extension office	0.00 (0.00)*
Value of oxen assets	0.00 (0.00)**
Value of non-oxen assets	0.00 (0.00)**
Had information on improved technology	0.61 (0.21)***
Had marketing information	0.86 (0.18)***
Own ox-cart	0.13 (0.31)
Member of farmer group	1.19 (0.29)***
Had access to off farm activities	0.02 (0.17)
Katete district	-0.30 (0.22)
Lundazi district	0.84 (0.20)***
Constant	-3.30 (0.52)
Summary statistics	
McFadden R^2	0.20
Model χ^2	207.02***
Log likelihood ratio	-426.56
Adopters correctly predicted	73%
Non-adopters correctly predicted	49%
Number of observations	810

*, **, and *** denotes significance level at 10%, 5% and 1% (Standard errors in parentheses).

It was found that group membership had a positive and significant effect on adoption of improved maize varieties. Social capital is indeed important for farmers in accessing inputs, group marketing of produce, input credit, savings and credit, seed production, soil and water conservation, and tree planting. According to van Bastelaer and Leathers (2006), it was found that social capital led to higher repayments of agricultural loans such as seeds and fertilizer in Zambia. Similarly, it was also found that cooperative membership had a strong positive impact on income[10] and on the adoption of fertilizer and improved seed in Kenya and Ethiopia, respectively (Abebaw and Haile, 2013; Alene *et al.*, 2008; Fischer and Qaim, 2012). This suggests that farmers can easily access inputs such as improved seed and fertilizer on credit, and sell farm produce as a group, if they belong to a farmers' group or cooperative.

Asset ownership has a significant and positive influence on adoption of improved maize varieties. If farmers have more assets, they can either convert these to cash or use them as collateral to obtain credit for the procurement of inputs such as improved seeds, fertilizers, herbicides, and pesticides.

The results further indicate that access to market information is significant and positively affects adoption of improved maize varieties. Easy access to and availability of market information play a major role in reducing high transaction costs to farmers in the quest to find markets for farm produce and inputs. If farmers have access to market information, the probability that they will adopt improved varieties is fairly high. This suggests that if farmers have access to markets and market information, then they more easily get maximum benefits from adoption of modern technologies.

Lundazi district dummy is statistically significant (relative to Chipata district) in explaining adoption of improved maize varieties. Farmers in Lundazi district are more likely to adopt improved maize varieties than those in other districts. This is consistent with the higher adoption rates of improved varieties in Lundazi (80%) compared with Chipata (56%) and Katete (51%) districts. The district dummy variable was included to account for possible heterogeneity in institutional support services, climatic conditions, and other factors affecting adoption of modern agriculture technologies. The greater adoption of improved maize in Lundazi may indicate its greater maize production potential, and the possible placement and concentration of support services in such high-potential districts.

[10] Active group members had positive income effects. However price advantages of collective marketing were small and high-value market potentials were not tapped. For more details see Abebaw and Haile (2013) and Fischer and Qaim (2012).

The welfare impacts of improved maize varieties

The correlation between adoption of improved farm technology and household welfare outcome variables is theoretically complex and there are further empirical pitfalls regarding the impact evaluation problem (Amare *et al.*, 2012). We estimated the impact of improved maize varieties on crop income, consumption expenditure, poverty status, and food security, using both propensity score matching (PSM)—nearest neighbor matching (NNM), and kernel-based matching (KBM),—and endogenous switching treatment regression (ESR).

Propensity score matching results

Before discussing the causal effects of maize technology adoption on the welfare of farmers, we want to investigate the quality of the matching process. After estimating the propensity scores for the adopters and non-adopters we checked the common support condition. Based on the results in table 3.5, column 2, the predicted propensity score for adopters ranged from 0.063 to 1.000 with a mean of 0.73 and from 0.037 to 0.977 for non-adopters with a mean of 0.49. Thus, using minima and maxima comparison the common support assumption is satisfied in the region of 0.063–0.977. This region of common support for the propensity scores is also clear from the density distribution for the two groups of adopters and non-adopters (figure 3.1). A visual inspection of the density distribution of the estimated propensity scores for the two groups indicates that the common support condition is satisfied: there is substantial overlap in the distribution of the propensity scores for adopters and non-adopters (figure 3.1). In addition, table 3.6 presents results from covariate balancing tests for the matching process which show that the standardized mean difference for overall covariates used in the estimation process of PSM reduced from 26.3% before matching to a range of 4.9%–6.2% after matching. The total bias also reduced in the range of 76%–81% through the matching process.

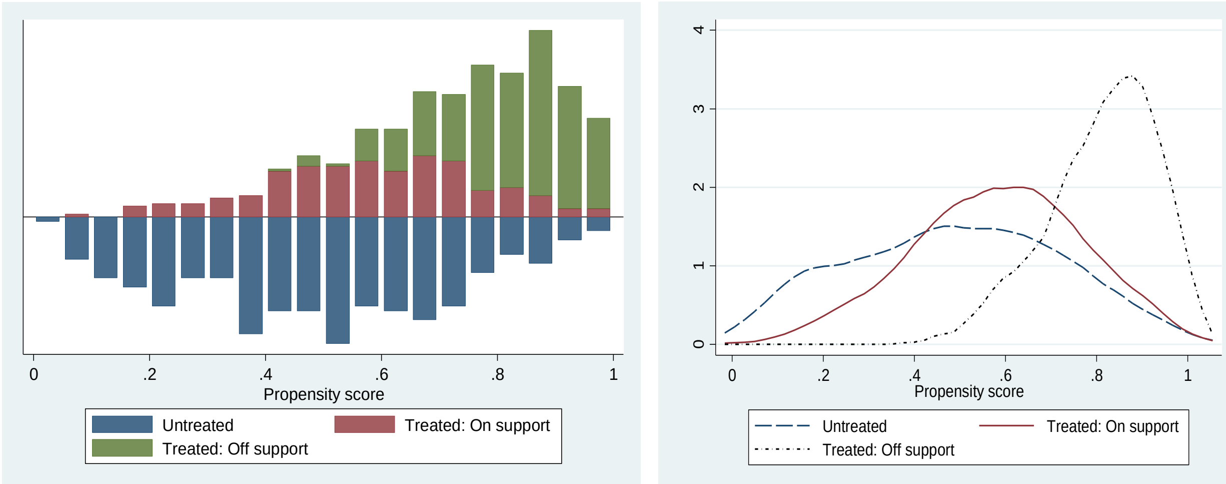

Figure 3.1: Propensity score distribution and common support for propensity score estimation.
Note: Treated on support indicates the individuals in the adoption group who find a suitable match, whereas treated off support indicates the individuals in the adoption.

Furthermore, the *p*-values of the likelihood ratio tests show the joint significance of all regressors in the logit model after matching, but not before matching. The pseudo-R^2 indicates how well the regressors explain the participation probability. It was further shown that the pseudo-R^2 reduced from 20% before matching to about 1.4% after matching and was fairly low, indicating that after matching there were no systematic differences in the distribution of covariates between both groups. The low pseudo-R^2, low mean standardized bias, high total bias reduction, and insignificant *p*-values of the likelihood ratio test after matching suggest that specification of the propensity score estimation process is successful regarding balancing the distribution of covariates between adopters and non-adopters.

Table 3.6: Matching quality indicators before and after matching

Matching algorithm	Outcome variable	Pseudo R^2		LR $\chi 2$		$p>\chi 2$		Mean standardized bias		Total % bias reduction
		Before matching	After matching	Before matching	After matching	Before matching	After matching	Before matching	After matching	
NNM	Net crop income ('000 ZMK/capita)	0.19	0.01	204.80	20.68	0	0.42	26.30	4.90	81
	Consumption expenditure ('000 ZMK/capita)	0.20	0.02	214.62	25.53	0	0.18	26.20	5.20	80
	Poverty (headcount ratio)	0.19	0.01	204.80	20.68	0	0.42	26.30	4.90	81
	Food security (yes=1)	0.19	0.02	204.80	24.08	0	0.24	26.30	5.70	78
KBM	Net crop income ('000 ZMK/ha)	0.19	0.02	204.80	21.90	0	0.35	26.30	5.30	80
	Consumption expenditure ('000 ZMK/capita)	0.20	0.02	214.62	25.75	0	0.17	26.20	5.70	78
	Poverty (headcount ratio)	0.19	0.02	204.80	21.90	0	0.35	26.30	5.30	80
	Food security (yes=1)	0.19	0.02	204.80	24.66	0	0.22	26.30	6.20	76

The PSM (NNM and KBM) estimates presented in table 3.7 shows that farmers who adopted improved maize varieties had increased crop income, consumption expenditure, food security, and reduced poverty levels. The increase in crop income per hectare ranged from ZMK2.3 million (US$448) to ZMK2.4 million (US$455), with an average crop income per hectare of US$425. The PSM results further show that adoption of improved maize varieties increased average consumption expenditure per capita in the range of ZMK271,122 (US$52) to ZMK305,122 (US$59).

Table 3.7: PSM estimates of the impact of maize variety adoption on crop income, consumption expenditure, food security and poverty status

Matching algorithm	Outcome variable	Means of outcome variables		ATT Difference
		Adopters	Non-adopters	
NNM	Net crop income ('000 ZMK/ha)	3658.59	1328.67	2329.92 (1354.60)*
	Consumption expenditure ('000 ZMK/capita)	1261.95	956.82	305.12 (174.42)*
	Poverty (headcount ratio)	0.62	0.73	-0.11 (0.05)**
	Food security (Food secure=1)	0.78	0.75	0.02 (0.04)
KBM	Net crop income ('000 ZMK/ha)	3658.59	1296.97	2361.62 (1389.19)*
	Consumption expenditure ('000 ZMK/capita)	1261.95	990.82	271.12 (129.67)**
	Poverty (headcount ratio)	0.62	0.73	-0.11 (0.04)**
	Food security (Food secure=1)	0.78	0.76	0.02 (0.05)

*, and ** denotes significance level at 10%, and 5% (Standard errors in parentheses).

Regardless of the matching algorithm used in PSM estimation, adoption of improved maize varieties reduces the probability of poverty by 11 percentage points. Adoption of agricultural technologies helps to increase crop productivity and crop income. Since crop income accounts for 74% of the total household income, technologies that boost crop productivity and address production and marketing constraints are crucial in reducing poverty and attaining food security. Other studies also established a significant link between adoption of new agricultural technologies and poverty reduction in Tanzania, Mexico, Bangladesh, and Kenya (e.g. Amare *et al.*, 2012; Becerril and Abdulai, 2010; Mendola, 2007; Mathenge *et al.*, 2014a).

Endogenous switching regression results

As the results of the PSM model may be biased due to unobservable factors, the ESR model was also used to check the robustness of the estimated effects obtained from the PSM model. Table 3.8 presents the ESR-based average treatment effects of adoption of improved maize varieties for a range of outcome variables—net crop income, consumption expenditure, poverty, and food security—under actual and counterfactual conditions. The ESR estimates of the determinants of crop income, consumption expenditure, poverty, and food security are presented in the appendix (table A3.1). The detailed ESR model estimates are not discussed due to space limitations, but it is interesting to note that the estimated coefficients on the selection terms are negative for non-adopters and positive for adopters, and were significantly different from zero, suggesting that there was self-selection in the adoption of improved maize in eastern Zambia.

The predicted outcome variables from ESR are used to examine the impact of improved maize by adoption category. The model is also used to validate PSM results regarding impact assessment of the improved varieties. The ESR-based average treatment effect estimates presented in table 3.8 are close to the PSM-based estimates. Results also show that adoption of improved maize varieties increases crop income, consumption expenditure, food security, and reduces poverty levels. In most cases, adopters would benefit more as compared to non-adopters. We are only discussing average treatment effects on the treated (ATT) and untreated (ATU) that are statistically significant from zero. The average increment on crop income per hectare for adopters (ATT) is ZMK78, 900 (US$15)—this is equivalent to US$36 (US$15*2.4) at farm level where 2.4 hectares is the average area planted to maize at household level for adopters. This implies that adopters would lose crop income of ZMK78, 900 per hectare had they not adopted improved maize varieties. Combining results from the two models, the increase in crop income per hectare ranges from ZMK78, 900 (US$15) using the ESR technique to ZMK2.4 million (US$455) using the PSM technique. The ESR results are relatively lower compared to the PSM results possibly due to unobservable factors which cannot be controlled for when using the PSM technique.

The average treatment effects (ATU) results from ESR also indicate that non-adopters would have achieved crop income gains of ZMK66,090 (US$12.7) per hectare had they adopted improved varieties. This empirical evidence is consistent with the gross margin analysis. Similarly, it is noted that adoption of improved maize varieties in the study area increased net income by 20% (see table 3.4). Crop income accounts for about 74% of total household income, and the remainder comes from livestock income and transfers such as remittances from abroad or from within the country. Maize accounts for 61% of the crop income. Given that 68% of the sample farmers sold maize, the crop can also be regarded as a cash crop in the study area. Smale and Mason (2014) also found that adoption of hybrid maize mainly through subsidy increased household income in Zambia.

Table 3.8: ESR-based average treatment effects of adoption of improved maize varieties in eastern Zambia

Means of outcome variable	Farm households type and treatment effects	Decision stage: To adopt	Decision stage: Not to adopt	Average treatment effects
Net crop income ('000 ZMK/ha)	Farm households that adopted (ATT)	396.65	317.75	78.90 (3.16)***
	Farm households that did not adopt (ATU)	365.85	299.77	66.09 (6.39) ***
Consumption expenditure ('000 ZMK/capita)	Farm households that adopted (ATT)	455.31	130.62	324.69 (2.30)***
	Farm households that did not adopt (ATU)	352.60	165.80	186.80 (23.00)***
Poverty status (%)	Farm households that adopted (ATT)	-50.08	-28.68	-21.40 (1.75)***
	Farm households that did not adopt (ATU)	-73.73	-55.52	-18.21 (2.73)***
Food security (%)	Farm households that adopted (ATT)	35.43	33.32	2.11 (2.29)
	Farm households that did not adopt (ATU)	43.96	22.53	21.43 (2.49)***

*** denotes significance level at 1% (Standard errors in parentheses).

The ESR model estimates show a higher impact on consumption expenditure per capita of ZMK324,690 (US$62) relative to the PSM estimates of ZMK305,122 (US$59). The advantage of ESR over PSM is that it can estimate the potential gain for non-adopters had they adopted the technology. Non-adopters would have increased consumption expenditure or gained household income per capita of ZMK186,800 (US$36) had they adopted improved maize varieties.

Consistent with the estimates of adoption on household income, the results further show that adoption of improved maize varieties can significantly reduce poverty levels in eastern Zambia. Adoption of improved maize varieties reduces the probability of poverty by 21 percentage points for adopters. For non-adopters, the ATU estimates show that the probability of poverty would have been 18 percentage points lower had they adopted the technology. The PSM results show that adoption of improved maize varieties reduces the probability of poverty by 11 percentage points, which is almost half the average treatment effect on the treated (ATT) from ESR. This could be attributed to unobserved heterogeneity which the PSM approach cannot account for.

Food security is one of most important welfare indicators related to agricultural technologies. Although insignificant, the ESR results show average treatment effects for adopters

(ATT), with adoption of improved maize varieties increasing the probability of food security by two percentage points. The ATU results based on ESR for food security also indicate that non-adopters would benefit more had they adopted improved maize varieties and the probability of food security would increase by 21 percentage points (table 3.8). Since most improved maize varieties are high yielding, resistant to pests and diseases, drought tolerant and many more advantages, adopters of such varieties are likely to get higher yields. Higher adoption rate of improved maize varieties and other agricultural technologies is highly associated with increased household food security particularly if most farm households get food from own production rather than other sources such as food purchase, food hunting from forests and lakes, and donation or gifts. Langyintuo and Mungoma (2008) also noted that the increase in the adoption rate and use intensity of improved maize varieties had subsequent impacts on food security and general livelihoods of households in Zambia. Shiferaw *et al.* (2014) also found that adoption of improved wheat varieties in Ethiopia increased food security. Therefore stimulating agricultural growth (thus reducing poverty and improving food security) in most agro-based economies such as Zambia primarily depends on the adoption of improved agricultural technologies, including improved maize varieties.

3.5 Conclusions

This chapter analyzes the determinants and welfare impacts of adoption of improved maize varieties in eastern Zambia using data obtained from a sample of over 800 farm households. The logit model estimates of the determinants of adoption of improved maize varieties showed that adoption is significantly related to education, group membership, access to extension advice and market information, household size, and ownership of oxen and non-oxen assets. The results suggest that adoption of improved maize varieties can be enhanced through increased access to information, markets, and productive assets. Easy access to market and availability of markets and information play a major role in reducing high transaction costs to farmers. However, access to reliable and competitive markets and information remains a challenge, possibly due to poor infrastructure and support services. Since both input and output markets are imperfect, there are emerging institutional innovations such as farmer cooperatives for collective marketing that reduce transaction costs.

Using both propensity score matching and endogenous switching regression models, the chapter further shows that adoption of improved maize leads to significant gains in crop income, consumption expenditure, and food security. The results further show that improved maize varieties had significant poverty-reducing impacts in eastern Zambia. Although the magnitude of the estimated effects varies across the two econometric methods, the qualitative results are similar. Adoption of improved maize varieties increased crop income per hectare and consumption expenditure per capita, and also reduced poverty levels and increased household food security by a probability of 11–21 and 2–21 percentage points, respectively. Higher adoption rate of improved maize varieties is associated with increased household food security if most farm households get food from own production rather than other sources i.e. food purchase. More importantly, the results showed that non-adopters would have gained from adoption of improved maize varieties. Therefore stimulating agricultural growth (thus reducing poverty and improving food security) primarily depends on the adoption of improved agricultural technologies like improved maize varieties. This point to the need for policies and strategies aimed at enhancing adoption of improved varieties among non-adopters through more efficient extension, credit, and input supply systems.

Appendix A3

Table A3.1: Endogenous switching regression estimates for crop income, consumption expenditure, poverty, and food security in eastern Zambia

Variables	Net crop income		Consumption expenditure		Poverty		Food security	
	Adopters	Non-adopters	Adopters	Non-adopters	Adopters	Non-adopters	Adopters	Non-adopters
Age of household head (years)	-0.01 (0.00)**	-0.01 (0.00)**	-0.00 (0.00)	-0.00 (0.00)**	0.01 (0.00) **	-0.00 (0.00)	-0.00 (0.01)	0.00 (0.00)
Head education 1-4 years	-0.05 (0.03)	-0.08 (0.03)**	0.02 (0.03)	-0.02 (0.03)	-0.06 (0.06)	0.03 (0.08)	-0.05 (0.07)	0.05 (0.07)
Head education 5-8 years	-0.00 (0.18)	-0.01 (0.01)	0.03 (0.01)***	-0.01 (0.01)	0.03 (0.03)	-0.02 (0.03)	-0.05 (0.03)*	-0.01 (0.03)
Head education 9-12 years	0.00 (0.10)	0.00 (0.01)	0.02 (0.01)***	0.01 (0.01)	-0.00 (0.01)	-0.01 (0.02)	-0.01 (0.02)	0.04 (0.03)
Head education > 12 years	0.03 (0.01)**	0.00 (0.03)	0.02 (0.01)*	-0.01 (0.02)	-0.02 (0.03)	0.09 (0.05)*	-0.02 (0.03)	0.55 (548)
Household size (number)	0.02 (0.01)*	0.00 (0.01)	-0.02 (0.01)**	-0.05 (0.01)***	0.09 (0.02) **	0.11 (0.03)***	-0.01 (0.02)	0.03 (0.03)
Rented in land (ha)	-0.03 (0.04)	0.17 (0.17)	0.11 (0.04)***	0.14 (0.14)	-0.29 (0.14) **	0.12 (0.30)	-0.16 (0.10)	-0.42 (0.50)
Contacts with extension agents	0.00 (0.00)***	0.00 (0.00)	0.00 (0.00)*	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.01)	0.01 (0.00)	0.02 (0.01)*
Contacts with NGO's extension agents	-0.00 (0.93)	0.00 (0.00)	0.00 (0.00)	0.01 (0.00)*	-0.00 (0.00)	-0.00 (0.01)	-0.00 (0.00)	0.04 (0.01)
Distance to main market (min)	0.00 (0.00)**	0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	-0.00 (00)	-0.00 (0.00)	0.00 (0.00)	-0.00(0.00)**
Log of non-oxen assets/capita	0.69 (0.57)	-0.04 (0.07)	0.02 (0.05)	0.09 (0.06)	-6.14 (1.71)***	0.33 (0.30)	7.58 (2.93)**	-0.14 (0.61)
Log of oxen assets/capita	0.05 (0.00)**	0.02 (0.03)	-0.05 (0.07)	-0.05 (0.11)	0.05 (0.00)	-0.06 (0.05)	0.02 (0.04)	0.13 (0.10)
Group membership			0.03 (0.09)	0.09 (0.06)				
Marketing information	0.09 (0.07)	0.01 (0.08)			0.32 (0.12)**	-0.19 (0.16)	-0.04 (0.17)	-0.29 (0.19)
Own bicycle	-0.06 (0.07)	0.13 (0.08)*	0.13 (0.05)**	-0.03 (0.19)	-0.12 (0.14)	-0.07 (0.19)	0.13 (0.15)	0.30 (0.19)
Own ox cart	0.12 (0.07)	0.10 (0.83)	3.76 (0.53)***	-0.10 (0.09)	0.04 (0.16)	0.23 (0.27)	-0.08 (0.19)	-0.220 (0.41)
Off farm activities	0.04 (0.05)	0.03 (0.12)	0.05 (0.01)***	0.01 (0.02)	-0.23 (0.11) **	-0.13 (0.15)	-0.17 (0.13)	0.16 (0.92)
Katete district	0.12 (0.08)	0.09 (0.17)			-0.16 (0.15)	0.02 (0.20)	0.40 (1.84)**	0.66 (0.17) ***
Lundazi district	0.12 (0.06)*	-0.13 (0.09)	0.18 (0.05)***	-0.28 (0.08) ***	-0.18 (0.10) *	0.12 (0.17)	0.03 (0.12)	-0.21 (0.20)
Constant	0.58 (412)	6.17 (0.53)***	-22.22 (3.87)***	6.54 (0.70) ***	44.01 (12.53)***	-1.28 (2.24)	-54.53 (21.47)**	0.22 (4.42)
Sigma	0.53 (0.02)***	0.46 (0.03)***	0.57 (0.02)***	0.67 (0.04)***	1.54 (0.39)***	13.47 (433)	-1.24 (1.31)	-0.71 (0.41)*
Rho	0.17 (0.72)	-0.28 (0.23)	0.93 (0.02)***	-0.97 (0.01)***	0.91 (0.00)***	1.00(0.00)***	-0.85 (0.32)**	-0.61 (0.26)**
Model diagnosis								
Wald χ2	37.66***		63.29***		172.30***		151.74***	
Log likelihood	-859.31		-868.30		-823.85		-825.65	
Number of observations	694		810		810		810	

*, **, and *** denotes significance level at 10%, 5% and 1% (Standard errors in parentheses).

CHAPTER 4

THE IMPACT OF IMPROVED MAIZE VARIETIES ON HOUSEHOLD FOOD SECURITY IN EASTERN ZAMBIA: A DOUBLY ROBUST ANALYSIS[11]

Abstract

This chapter investigates the impact of improved maize varieties on household food security in eastern Zambia using household survey data from a sample of over 800 rural households. Since treatment effect estimates are often prone to misspecification in either the treatment or outcome equation, we use the doubly robust inverse probability weighted regression adjustment method, complemented with propensity score matching on six different food security measures to obtain reliable impact estimates. Generally, we find a positive impact of improved maize adoption on food security across the two econometric approaches.

Key words: Improved maize varieties; food security; inverse probability weighted regression; propensity score matching; Zambia.

[11] Manda, J., Gardebroek, C., Alene, A.D., Kuntashula, E. (2015). The impact of improved maize varieties on household food security in eastern Zambia: A doubly robust analysis. Submitted to the *Journal of Development Effectiveness.*

4.1 Introduction

Sustainable agricultural production is important in reducing poverty and food insecurity in Sub-Saharan African countries. With rapidly rising populations and often slow growth in agricultural productivity, most African countries are exposed to recurrent food emergencies and the uncertainties of food aid; hence, increasing and stabilizing domestic production of food staples is essential for food security (World Bank, 2007). Although in recent years agricultural production has improved, climate change, environmental degradation, limited adoption of improved agricultural technologies, and global food price volatility threaten the improvements gained, maintaining food insecurity in Africa (World Bank, 2007).

In Zambia, agriculture is a priority sector in achieving sustainable economic growth and reducing poverty and food insecurity. The sector supports the livelihoods of over 70% of the population and contributes about 15% to the national gross domestic product (Kalinda *et al.*, 2014a; Sitko *et al.,* 2011). Maize is Zambia's principal food staple, accounting for about 60% of national calorie consumption and serving as the dietary mainstay in central, southern, and eastern Zambia (Dorosh *et al.,* 2009). Its primacy has grown steadily as the result of past government policies that have encouraged the production of maize in all parts of the country (Kumar, 1994). In some cases, farmers sell surplus maize and according to Jayne *et al.* (2010), maize is the single most important crop in smallholder farm income with gross income of about 41% attributed to it. The majority of the maize is produced by smallholder farmers in rural areas who make up about 80% of the entire maize production in Zambia (Sitko *et al.*, 2011).

According to Kalinda *et al.* (2014) increasing maize productivity and incomes of smallholders, both of which have remained very low, is a major challenge facing Zambia. Improving the productivity and production of maize through generation and development of improved maize varieties could be an important approach to achieve broad-based economic growth, food security and poverty reduction in Zambia. Over the last decade, a number of organizations such as the International Maize and Wheat Improvement Center (CIMMYT) and the International Institute of Tropical Agriculture (IITA) have been working with the Zambia Agricultural Research Institute (ZARI) to develop and disseminate improved maize varieties. Private seed companies such as Panner, SeedCo and Maize Research Institute (MRI) have also invested in maize breeding. Currently, smallholder farmers in Zambia use more than 30 improved maize varieties.

In recent years a number of studies have looked at the welfare impacts of improved maize varieties in Zambia (Kumar, 1994; Mason and Smale, 2013; Smale and Mason, 2014), but most of the previous studies have not measured the direct impacts on household food security. An exception is the paper by Khonje *et al.* (2015) that looks at the impacts of improved maize in eastern Zambia, including one food security variable. They find that improved maize is important in increasing income and reducing poverty. However, using a single measure of household food security, they find a rather weak association of improved maize adoption with household food security. This chapter extends the work done by Khonje *et al.* (2015) by explicitly examining the impact of adoption of improved maize varieties on household food security in eastern Zambia[12] using several food security measures that capture various aspects of food security. In addition, instead of using total household consumption expenditure as used in Khonje *et al.* (2015), this chapter uses food expenditure as measure of food security. It adds value to existing literature on adoption and food security in the following ways. First, unlike other semi-parametric impact evaluation methods, this chapter uses the Inverse Probability Weighted Regression Adjustment (IPWRA) estimation method (Imbens and Wooldridge, 2009; Wooldridge, 2010). This method provides efficient estimates by allowing the modelling of both the outcome and the treatment equations and requires that only one of the two models is correctly specified to consistently estimate the impact. This allows us to control for selection bias at both the treatment and outcome stages, a property commonly referred to as “doubly robust”. We complement our results by also estimating the impacts of improved maize using the semi-parametric propensity score matching (PSM). Second, this is the first work to our knowledge to rigorously analyse the impact of improved maize varieties on food security in Zambia using both objective and subjective measures of food security. The per capita food expenditure and the food security line derived from the cost of calories method constitute the objective measures, while the respondents’ own perceptions about their food security status constitute the subjective measures. Recent studies by Mallick and Rafi (2010), Kassie *et al.* (2014a), Kassie *et al.* (2014b) and Shiferaw *et al.* (2014) used subjective measures of household food security in Bangladesh, Kenya, Tanzania, and Ethiopia, respectively. Deaton (2010) also advocates for the use of self-reported measures of poverty in surveys. However, a moral hazard risk with subjective measures

[12] An adopter in this study is defined as any farmer who planted or allocated land to at least one improved maize varieties.

of food security is that if the respondents expect that answers will influence the potential for support from the government or a project (Pinstrup-Andersen, 2009), they may give answers that do not truly reflect their food security situation. To overcome this problem, we use both objective and subjective food security measures in this chapter.

The remainder of the chapter is a follows. Section 2 presents an overview of improved maize adoption in Zambia. Section 3 provides a discussion on the conceptual and empirical frameworks, while section 4 presents the data and description of variables. Section 5 presents the empirical results, whereas the last section draws conclusions.

4.2 Adoption of improved maize varieties in Zambia

Improved maize varieties in Zambia consist mainly of hybrids and open-pollinated varieties (OPVs). A hybrid maize variety results from crossing two or more inbred lines, while OPVs are populations that breeders have selected for a very specific set of traits and generally they can be replanted up to three years without a decline in yields (Becerril and Abdulai, 2010). Hybrid maize varieties were introduced to Zambian smallholder famers around the 1970s and to date about 60% of the smallholders use hybrid maize seed in Zambia (Kumar, 1994; Tembo and Sitko, 2013).

Some of the most popular hybrid and OPVs that are common among farmers in the Eastern province of Zambia include MRI 621, SeedCo 513, Pan 53 and Pool 16 (OPV). Most of these varieties have been known to produce high yields and are resistant to diseases and insects. The production of maize in eastern Zambia is entirely rain fed, hence, most of the medium-maturing varieties (125–140 days) are suitable for the province, which falls in the agro-ecological region II (middle rainfall area) receiving rainfall in the range of 800–1000 mm per year. For instance, Pan 53 is a medium-maturing hybrid variety produced by the Pannar Seed Company; it is tolerant to diseases such as grey leaf spot and the maize streak virus and has a yield potential of about 10 metric tons per hectare.

Recent studies have shown that improved maize varieties have the potential of increasing yields and income for smallholder farmers in Zambia (Hamazakaza *et al.*, 2013; Smale and Mason, 2014). Unlike previous studies, in this chapter we specifically examine the impact of improved maize varieties (including both hybrids and OPVs) on household food security in eastern Zambia, which is an important maize growing area. We present different estimates of improved maize adoption on food security based on the different food security measures.

4.3 Conceptual and empirical frameworks

An important objective of this chapter is to analyse the impact that adoption of improved maize has on smallholder farmers' food security status. This can be measured by the average treatment effect on the treated (ATT), defined as the average difference in outcomes of improved maize adopting households, with and without the technology (Takahashi and Barrett, 2013):

$$ATT = E\{Y_{iA} - Y_{iN} | T_i = 1\},$$
$$= E(Y_{iA} | T_i = 1) - E(Y_{iN} | T_i = 1) \quad (1)$$

where $E\{.\}$ is the expectation operator, Y_{iA} and Y_{iN} are the outcomes in the two counterfactual situations of adoption and non-adoption respectively, and T_i is the treatment indicator, equal to 1 if the household adopted improved maize varieties and 0 otherwise. The problem in equation (1) is that it is not possible to observe the outcome of improved maize adopters had they not adopted, i.e. $E(Y_{iN} | T_i = 1)$. However, replacing these unobserved counterfactuals by outcomes of non-adopters ($E(Y_{iN} | T_i = 0)$) may result in biased ATT estimates (Takahashi and Barrett, 2013).

To solve this problem we use the Inverse Probability Weighted Regression Adjustment (IPWRA) estimation method proposed by Wooldridge (2010) as our primary estimator. The IPWRA estimator uses the inverse of the estimated treatment-probability weights to estimate missing data corrected regression coefficients that are subsequently used to produce robust estimates of ATT.

The inverse probability weights (IPW) are calculated by weighting the observations based on the inverse probability of being treated. The probability of receiving treatment (propensity score) is defined by Rosenbaum and Rubin (1983) as:

$$p(X) = \Pr(T_i = 1 | X) = F\{h(X)\} = E(T_i | X) \quad (2)$$

where X is the multidimensional vector of pre-treatment covariates based on observed characteristics and $F\{.\}$ is a cumulative distribution function. The vector X includes household characteristics, social capital, and information and location variables that relate to treatment. The propensity scores generated in equation (2) are used to create a synthetic sample in which the distribution of measured baseline covariates is independent of treatment assignment. Using simple inverse weights equal to 1 for the treated and $\frac{\hat{p}(X)}{(1-\hat{p}(X))}$ for the non-treated, then following Hirano and Imbens (2001), weights can be defined in a combined way as:

$$w_i = T_i + (1 - T_i)\frac{\hat{p}(X)}{1-\hat{p}(X)} \tag{3}$$

where $\hat{p}$ are the estimated propensity scores.

The regression adjustment (RA) approach on the other hand uses a linear regression model for treated and non-treated units and averages the predicted outcome (in this case food security status of each farmer under adoption and non-adoption) to obtain treatment effects. One could say that RA concentrates on outcomes and IPW focuses more on treatment in calculating treatment effects. Following Wooldridge (2010), the ATT for the regression adjustment (RA) model can be expressed as:

$$ATT_{RA} = n_A^{-1} \sum_{i=1}^{n} T_i [r_A\,(X, \delta_A) - \ r_N(X, \delta_N)] \tag{4}$$

where n_A is the number of adopters and $r_i(X)$ is the postulated regression model for the adopters (A) and non-adopters (N) based on observed covariates X and parameters $\delta_i = (\alpha_i, \beta_i)$.

The IPWRA estimator is constructed by combining the regression adjustment (equation 4) with weighting (equation 3). As Wooldridge (2010) mentions, one only needs to correctly specify either IPW or the RA model to obtain reliable treatment effect estimates, conditional on the given covariates. For instance if the treatment model is not specified correctly, but the outcome model is, we still obtain correct estimates of the treatment effects. Similarly, if the outcome model is correctly specified and the treatment model is not, unbiased estimates of ATT are still going to be obtained. Formally, the ATT for the IPWRA estimator can be expressed as:

$$ATT_{IPWRA} = n_A^{-1} \sum_{i=1}^{n} T_i [\ r_A^*(X, \delta_A^*) - \ r_N^*(X, \delta_N^*))] \tag{5}$$

where $\delta_A^* = (\alpha_A^*, \beta_A^*)$ is obtained from a weighted regression procedure

$$\min_{\alpha_A^*, \beta_A^*} \sum_{i=i}^{N} T_i \left(y_i - \alpha_A^* - X\beta_A^*\right)^2 \Big/ \hat{p}(X, \hat{\gamma}) \tag{6}$$

and $\delta_N^* = (\alpha_N^*, \beta_N^*)$ is obtained from the weighted regression procedure

$$\min_{\alpha_N^*, \beta_N^*} \sum_{i=i}^{N} (1 - T_i)\left(y_i - \alpha_N^* - X\beta_N^*\right)^2 \Big/ \left(1 - \hat{p}(X, \hat{\gamma})\right) \qquad (7)$$

So, compared to ATT based on RA, ATT for IPWRA has a similar expression except that different (weighted) estimates are used for the regression parameters (Wooldridge, 2010: 931).

Suffice to mention that the IPWRA method relies on two assumptions often made in estimating treatment effects. The first assumption is the Conditional Independence Assumption (CIA) or Unconfoundedness, which states that once we condition on a rich set of covariates, treatment assignment is essentially randomised. This is a strong and controversial assumption in that self-selection into treatment might still be based on unobservables (Wooldridge, 2010). However, we try to reduce the selection on unobservables by conditioning on a rich set of covariates that we have in our data set in equation (2). A second assumption is that conditioning on a set of covariates, each individual has a positive probability of receiving treatment (also known as the overlap assumption). If this assumption is satisfied, it guarantees that for each adopting household in the sample, we observe some non-adopting households with similar covariates[13].

Since there are several methods that are used in estimating treatment effects, Imbens and Wooldridge (2009) recommend the use of several approaches to estimate treatment effects in order to check the robustness of the results. As a key robustness check, we also used the propensity score matching (PSM). PSM is one of the most popular methods for impact evaluation and although the IPWRA estimator is based on more or less the same assumptions as PSM, the two methods, differ in that; (1) PSM solves the problem of missing data by matching on propensity scores, while IPWRA corrects for the same problem by weighting on propensity scores, and (2) The IPWRA estimator gives two opportunities for adjusting for the hidden selection effects of confounding by combining inverse probability weighting with regression adjustment, while matching is based only on the treatment or propensity score model.

Although the IPWRA is robust to misspecification of either the treatment equation (propensity score) or the outcome equation, it does not control for selection on unobservables (unobserved heterogeneity). To assess whether selection on unobservables has an effect on our results, we use the Rosenbaum bounds (Rosenbaum, 2002) to assess how sensitive our results are to unobserved factors.

[13] We provide a test for the overlap assumption in section 5.

4. 4 Data and description of variables

4.4.1 Sampling scheme

The data used in this chapter come from a survey of 810 sample households conducted in January and February 2012 in the Eastern Province of Zambia. This survey was conducted by the IITA and CIMMYT in collaboration with the ZARI for the project Sustainable Intensification of Maize–Legume Systems for the Eastern Province of Zambia (SIMLEZA). A survey questionnaire was prepared and administered by trained enumerators, who collected data from households through personal interviews. The survey was conducted in three districts in eastern Zambia—Chipata, Katete, and Lundazi—which were targeted by the project as the major maize and legume growing areas. In the first stage, each district was stratified into agricultural blocks (8 in Chipata, 5 in Katete and 5 in Lundazi) as primary sampling units. In the second stage, 41 agricultural camps were randomly selected, with the camps allocated proportionally to the selected blocks and the camps selected with probability of selection proportional to size. Note that a camp is a catchment area made up of 8 different zones comprising of villages, and is headed by an agricultural camp officer. A block on the other hand is made up of camps and is managed by an agricultural block officer. Overall, 17 camps were selected in Chipata, 9 in Katete and 15 in Lundazi. A total sample of 810 households was selected randomly from the three districts with the number of households from each selected camp being proportional to the size of the camp.

4.4.2 Food security measurement

In this chapter we use both objective and subjective food security measures. The objective measures include the per capita food expenditure and a binary food security variable (derived from the cost of calories method explained below). The subjective measures include the households' self-reported food security measures which include food surplus, breakeven food security, occasional food insecurity and chronic food insecurity variables. Some of the variables such as chronic food insecurity had very few observations hence, we generated another subjective food security variable, which is a binary indicator constructed from the four categorical variables mentioned above

The cost-of-calories method proposed by Greer and Thorbecke (1986) was used to determine the food security line from which the food security variable was derived. The line can be considered as the minimum food expenditure necessary for a person to maintain a minimum level of nutrition necessary for healthy living. In accordance with the Central Statistics Office (CSO) of Zambia, we use 2100 calories per person per day as the minimum calorie requirement. Per capita food expenditure (E) in logs can be linked to calorie intake (C) via:

$$lnE = a + bC \tag{8}$$

The estimated cost of obtaining the mean energy requirement deemed adequate for human survival is then approximated by:

$$F = e^{(\hat{a}+M\hat{b})} \tag{9}$$

Where $\hat{a}$ and $\hat{b}$ are the estimated coefficients from equation (8) and M is the minimum calorie requirement (2100 kcal). Therefore, a household with a food expenditure above F is considered to be food secure and those below, food insecure.

The second objective food security measure is per capita food expenditure, which includes the total food purchased by the household, the consumption of food produced by the household, and any food received by the household either through aid or in-kind.

The subjective food security measure is based on the perception of the respondents about their own food security status. Based on own food production, food purchases, and aid from different sources, respondents were asked how they perceived their food security situation in the year preceding the survey. The respondents categorized the food security status of their households into the four subjective sub-measures mentioned above. Occasional or transitory food security refers to a situation when a person suffers from a periodic decline in food consumption, while permanent or chronic food insecurity describes a long-term lack of access to sufficient food (Pinstrup-Andersen, 2009). Breakeven food security on the other hand is a situation where a household has no food shortage or surplus. Following Mallick and Rafi (2010) we constructed the subjective binary food security measure as follows: we combined the chronic and occasional food insecurity variables to define “food insecure households”, while the breakeven and food surplus variables were combined to classify “food secure households”. Note that in this chapter, we do not distinguish between food and nutrition security[14]. The food security indicators above mainly measure access to and availability of food.

It is important to mention that subjective measures of food security have both advantages and disadvantages. One of the benefits of these measures is the relative low cost of capturing them, compared with expensive expenditure data required to compute calorie consumption estimates (Headey and Ecker, 2013). Second, Headey and Ecker (2013) argue that subjective indicators of food security can also capture psychological dimensions of food insecurity since household's perceptions matter in their own right. Third, since respondents were asked as to how they perceived their food security situation in the last 12 months, the subjective measures are capable of capturing seasonality and other short-run food price movements (Headey, 2013a).

One of the challenges of self-reported subjective measures is that they tend to be biased towards overestimating food insecurity in comparison with quantitative methods. Secondly, unlike quantitative measures, subjective data do not provide much information about the size of welfare impacts (Headey, 2013).

4.4.3 Specification of variables in the treatment and outcome models

The covariates used in the estimation of the probability of adoption are based on theory and studies on adoption of improved or modern agricultural technologies (Alene *et al.*, 2000; Feder *et al.*, 1985; Isham, 2002; Kassie *et al.*, 2011). The variables included can be summarized as follows; (1) Household and farm variables: age, gender, education of the household head, household size, dependency ratio, total livestock units (TLU)[15], access to credit, total off-farm income, and land size; (2) Social capital and networking variables: kinship; (3) Government support variable: reliance on government support (safety nets); (4) Information variable: information on output markets and prices, and number of contacts with extension agents; (5) Locational variables: rainfall index, distance to extension office and output markets. We explain the hypothesised relationships for selected variables with the outcome variables below.

A number of studies have shown that age of the household head can affect technology adoption. Older farmers are expected to have more experience in growing improved maize

[14] According to Frankenberger *et al.* (1997) a person is considered nutrition secure when "she or he has a nutritionally adequate diet and the food consumed is biologically utilized such that adequate performance is maintained in growth, resisting or recovering from disease, pregnancy, lactation and physical work".
[15] TLU was calculated as: TLU = (cattle + oxen) × 0.5 + (goats + sheep + chickens+ rabbits) × 0.1 + pigs × 0.2.

varieties and may also accumulate more personal capital to enable them to invest in modern technologies. On the other hand very old farmers may not have the energy and desire to adopt modern agricultural technologies. Uaiene *et al.* (2009) noted that younger household heads may be suppler and therefore are also likely to adopt new technologies. We therefore expect the sign of the coefficient on age to be either positive or negative (indeterminate).

The gender of the household head is a dummy variable that takes the value of 1 if the head of the household is male, and 0 if female. Some studies in Africa have found that female headed household are less likely to adopt modern agricultural technologies compared to their male counter parts (Tanellari *et al.*, 2013). This is so because women are generally believed to be discriminated against in terms of access to resources, inputs and information on improved agricultural technologies. We hypothesise therefore that male-headed households are more likely to adopt improved maize varieties.

Education plays an important role in technology adoption in that it enables households to interpret new information and understand the importance of adopting modern agricultural technologies. Availability of land on which to grow an improved maize variety can also affect adoption decisions (Feder *et al.*, 1985). Farmers can only allocate a larger area to improved varieties if they have enough land; as such, those with more land have a comparative advantage to adopt improved maize varieties. Hence, we expect both education and land to be positively correlated with improved maize adoption. Similarly, we expect TLU and access to credit to be positively related with adoption of improved maize varieties. Farmers who have more livestock holdings (TLU) and those who are able to access credit tend to be more productive and resilient to shocks and are therefore more likely to adopt improved agricultural technologies.

The dependency ratio is defined as the ratio of prime-age adults to the total number of persons in the household outside the economic active population (children under the age of 15 and adults above 65 years). The ratio is most often used to measure the pressure on the productive population. We therefore expect adoption to be negatively related with the dependency ratio.

Social capital is said to be the glue that holds societies together and without it there can be no economic growth or human well-being. Social capital in rural households is associated with faster rates of technology adoption and improved agricultural productivity (Isham, 2002).

Kinship represents the number of relatives in and outside the village that a household can rely on for critical support.

Most governments provide aid or subsidies when crop production fails (social safety nets) in order to smoothen consumption and increase productivity (Barrett, 2001; Kassie *et al.*, 2013). Safety nets play an important role in boosting demand for products, alleviating liquidity constraints for smallholder farmers, and fostering income-generating strategies (Devereux *et al.*, 2008). Thus we expect such programmes to influence adoption in a positive way.

One of the major reasons that make smallholder farming systems less productive and profitable is the information and skills gap that constrains the adoption of available technologies and management practices (World Bank, 2008). Adegbola and Gardebroek (2007) included farmer's contacts with extension agents as a proxy for information. Farmers who have regular contacts with extension agents are in a better position to gather useful information regarding benefits of modern agricultural technologies. We therefore envisage that contacts with extension agents will be positively correlated with improved maize adoption. Similarly information about the availability of markets where to sell the maize and about output prices is expected to have a positive effect on maize adoption. Availability of information on markets and prices can enable a farmer to know in advance whether adopting a particular agricultural technology would be profitable or not.

The distance to extension agent's office and output markets reflects the cost of obtaining information as well as the cost of taking produce to the market. According to Kassie *et al.* (2013) the distances can also affect the availability of new technologies, information, credit institutions, etc. Hence, we posit that the further away the extension office and output markets are, the less likely a famer will adopt improved maize technologies. The coefficients on the distance of the village to the nearest agent's office or output markets are therefore expected to be negative.

Since similar variables are used in the outcome model as in the treatment model, below, we highlight how we expect the variables will affect household food security a priori. Based on the literature on food security (Alene and Manyong, 2006; Kassie *et al.*, 2014b; Mallick and Rafi, 2010) we expect the food security status to improve with gender, area cultivated, kinship, reliance on government support, access to credit, off-farm income, and rainfall. On the other hand, we expect the dependency ratio, distances to the extension agent's office and output markets to have a negative relationship with food security. For reasons mentioned above we expect age of the household head to be indeterminate. Similarly, we expect the coefficient on the size of the household to be either positive or negative. It may take a positive sign if household members are productive and therefore contribute effectively to the economic activities that a household is engaged in; it may be negative if the household consists mainly of unproductive members, such as very old people and young children.

4.4.4 Descriptive statistics

Descriptive statistics of the variables used in the analysis are presented in table 1. Based on the food security line of ZMK479,260 ($92[16]) per year, 49% of the surveyed households were food secure, which was much lower than the subjective food security (75%). The statistics in table 1 also show that based on the respondents own perception of food security, about 51% had food surpluses, 21% experienced transitory food insecurity and only 2% experienced chronic food insecurity.

We further show in table 4.1 that maize is one of the most important crops grown in Zambia. Results show that on average 64% of the households adopted improved maize varieties and accounted for 45% of the total area cultivated by the sample households. The social capital and networking data collected in the study include the number of relatives that a farmer has inside and outside the village, and group membership. Data on government support is reflected by the farmers' perceptions of government assistance, equal to 1 if the farmers believe that they can depend on government support during crop failure with about 77% trusting in government help in times of crop failure. A rainfall index was also constructed based on the data collected in the above mentioned survey to capture the famers' perceptions on the distribution of rainfall over the past three seasons. The index was constructed based on the farmer's responses on whether rainfall came and stopped on time, whether there was enough rain at the beginning of and during the growing season, and whether it rained near harvest for the past three seasons. The yes or no responses to these questions were then coded as "good" or "bad" rainfall outcomes, and averaged over the number of questions asked (five questions) so that the best outcome would be equal to one and the worst equal to zero. On average, about 68% of the respondents considered the rainfall for the past three years as favourable.

[16] Exchange rate at the time of the survey: 1US$=ZMK5,197.

Table 4.1: Variable definitions and summary

Variable	Definition	Mean	Std.dev
Dependant variables			
Food expenditure	Expenditure on food items per capita (ZMK'000,000)	4.62	5.66
Objective food security	1 = Food secure	0.49	0.50
Subjective food security	1 = Food secure	0.75	0.44
Food surplus	1= Food surplus	0.51	0.50
Break even food security	1= Breakeven food security	0.23	0.42
Occasional food insecure	1= Occasional food insecure	0.21	0.41
Chronic food security	1= Chronic food insecure	0.02	0.15
Treatment variable			
Improved maize varieties	1= Improved maize varieties	0. 64	0.46
Explanatory variables			
Age of head	Age of household head (years)	43.01	14.23
Gender of head	Gender of household head (1= male)	0.64	0.48
Education of head	Education of household head (number of years)	6.24	3.58
Household size	Size of the household (number)	6.97	3.12
Dependency ratio	Proportion of household members that are aged 0-15 years and above 65 years (dependents) to those that aged 16-65 years.	1.16	0.84
Land per capita	Total land cultivated (ha) per capita	0.56	0.59
Area under improved maize	Total area planted with improved maize (ha)	1.16	2.36
Area under improved maize (%)	Percent area under improved maize	45.03	40.61
Off farm income	Non-farm income (ZMK 000,000)	3.22	8.95
Kinship	Kinship (number of relatives that farmer has inside the village)	4.00	6.65
TLU	Livestock holdings in Total Livestock Units (number)	3.79	4.14
Safety nets	Rely on government safety nets if crop fails (1= yes)	0.79	0.41
Market information	Had information on markets and prices (1 = yes)	0.65	0.48
Contacts	Number of contacts with extension agents (number)	16.00	28.89
Credit	Access to credit (1= yes)	0.76	0.43
Rainfall	Rainfall index (1 = best)	0.68	0.47
Distance to extension agent	Distance to extension agent office (minutes)	65.61	71.57
Distance to market	Distance to nearest village market (minutes)	52.16	80.20

Descriptive statistics show that households with larger areas under improved maize varieties are on average more food secure than those with smaller farms (table 4.2). In table 4.2, the lowest quintile represents 25% of the households with smallest area under improved maize varieties while the highest quintile represents the 25% of the households with the largest area of cultivated land. Without making any causal inferences, the results shows that as the land under improved maize varieties increases, both the objective and subjective food security measures show a corresponding increase in the number of households that are food secure.

Table 4.2: Food security status by area under improved maize adoption

Quintiles based on area under improved maize	Per capita food expenditure (ZMK`000)	Objective food security dummy	Subjective food security dummy	Food surplus	Breakeven food security	Occasional food insecurity	Chronic food insecurity
Lowest	175	0.33	0.69	0.41	0.28	0.26	0.02
Middle	460	0.47	0.70	0.46	0.24	0.27	0.13
Upper	597	0.58	0.74	0.56	0.19	0.21	0.03
Highest	790	0.67	0.87	0.68	0.19	0.11	0.02

In most of Sub-Saharan Africa, female-headed households in rural areas are often more prone to food insecurity as well as poverty than male-headed households. Even though the percentage of male-headed households that were food secure was higher than those headed by females, there was no significant difference between male- and female-headed households with regards to the objective food security measures (table 4.3). However, the food surplus results reveal that more female-headed households suffered from food insecurity as compared to their male counterparts. Similarly, the results show that more female headed household experienced chronic food insecurity than men. One possible reason for this difference is that men and women respond differently to subjective food security questions and Coates *et al.* (2010) attribute this to the different responsibilities within the same household, power imbalances influencing intra-household food allocation and because men seem to take a more psychological responsibility for ensuring food supply.

Table 4.3: Average differences in outcome variables between male– and female–headed households

Outcome variable	Male (n = 520)	Female (n = 290)	Mean difference
Ln Per capita food expenditure (ZMK`000)	519	451	68 (47.9)
Objective food security dummy	0.51	0.46	0.05 (0.03)
Subjective food security dummy	0.76	0.72	0.05 (1.45)
Food surplus	0.54	0.46	0.08 (0.04)**
Breakeven food security	0.22	0.26	-0.04 (1.16)
Occasional food insecurity	0.21	0.22	-0.01 (0.37)
Chronic food insecurity	0.01	0.04	-0.04 (3.28)***

, and * denotes significance level at 5% and 1% (Standard errors in parentheses).

4.5 Empirical results

4.5.1 Propensity scores

In section 4.3 it was explained that our IPWRA estimator for ATT requires estimation of propensity scores. These are based on a probit model and the parameter estimates of this model are presented in table 4.4. As noted by Takahashi and Barrett (2013), propensity score estimation only serves as a method to achieve a balance between the observed covariates across the adopters and non-adopters. Hence no causal interpretation will be inferred from the results in table 4.4. Although detailed interpretation of the propensity scores is not undertaken, a number of variables were significant and had the expected signs.

Table 4.4: Probit model estimates of adoption of improved maize varieties

Explanatory variables	Coefficients
Age of household head	0.00 (0.00)
Gender of household head	-0.23 (0.11)***
Education of household head	0.05 (0.01)***
Household size	0.06 (0.02)***
Dependency ratio	-0.14 (0.06)**
Kinship	0.02 (0.01)*
Credit	-0.11 (0.12)
Land per capita	0.35 (0.12)***
Ln off- farm income	0.01 (0.01)
TLU	0.04 (0.02)***
Safety nets	-0.17 (0.13)
Market information	0.62 (0.10)***
Contacts	0.00 (0.00)
Rainfall index	-0.10 (0.11)
Ln Distance to extension office	-0.02 (0.04)
Ln Distance to village market	0.03 (0.03)
Lundazi district	0.41 (0.12)***
Katete district	-0.24 (0.13)**
Constant	-0.97 (0.36)**
Model diagnostics	
Pseudo R^2	0.18
Count R^2	
Wald chi2(18)	145.45
N	810

*, **, and *** denotes significance level at 10%, 5% and 1% (Robust standard errors in parentheses).

Results in table 4.4 show that gender, education, cultivated land, household size, dependency ratio, kinship, total livestock (TLU) and market information and the Lundazi and Katete district dummies were significantly correlated with the conditional probability of adopting improved maize. The results imply that educated farmers tend to have greater aptitude to decipher new information and analyse the importance of new technologies which helps in decision making when it comes to adopting improved technologies. Farmers who have more livestock holdings have a higher propensity to adopt improved maize varieties because they are usually more productive as they can, for instance use oxen labour for land cultivation as well as transportation of inputs. Significance of the district dummy variables (with Chipata district as a reference district) likely reflects unobservable differences in terms of the resources and weather patterns.

For IPWRA results to have a causal interpretation, the observations have to satisfy the overlap and unconfoundedness assumptions (Schminke and Biesebroeck, 2013). When the overlap assumption is violated, estimators are sensitive to the choice of specification and it may lead to imprecise estimates (Crump *et al.*, 2009). We compute the normalized differences for each covariate (Imbens and Wooldridge, 2009; Wooldridge, 2010) to assess the overlap assumption. The normalized differences were calculated as:

$$norm\_diff_j = \frac{(\bar{X}_{1j} - \bar{X}_{0j})}{\sqrt{s_{1j}^2 + s_{0j}^2}}$$

Where $\bar{X}_{1j}$ and $\bar{X}_{0j}$ are the means for the covariate j for the adopters and non-adopters, while S_{1j} and S_{0j} are the estimated standard deviations. Imbens and Rubin (2010) suggest that normalised differences above the absolute value of 0.25 should be a cause for concern and the results in table 4.5 shows that only 4 of the values in *X* exceed the absolute value of 0.25. This suggests that the specification in equation (5) is valid to derive ATT estimates.

Table 4.5: Assessing overlap assumption (Normalized differences)

	Non-adopters	Adopters	Normalized
	Mean	Mean	difference
Age of household head	41.86	43.65	0.09
Gender of household head	0.64	0.64	0.01
Education of household head	5.26	6.80	**0.30**
Household size	6.33	7.33	0.23
Dependency ratio	1.28	1.09	-0.16
Kinship	3.43	4.33	0.10
Credit	0.78	0.75	-0.06
Land per capita	0.45	0.63	0.23
Ln off- farm income	8.25	8.96	0.07
TLU	2.74	4.39	**0.29**
Safety nets	0.83	0.77	-0.11
Market information	0.48	0.75	**0.38**
Contacts	11.92	18.23	0.16
Rainfall index	0.68	0.67	-0.02
Ln Distance to extension office	3.61	3.61	0.00
Ln Distance to village market	2.67	2.97	0.12
Lundazi district	0.20	0.46	**0.37**
Katete district	0.31	0.17	-0.22
N	293	517	

Bold values indicate difference of more than 0.25.

4.5.2 Determinants of food security (outcome model)

Although the main objective of this chapter was to evaluate the impacts of improved maize adoption on food security, we discuss briefly the determinants of food security presented in table 4.6. Results are presented for the three[17] food security measures and separated for adopters and non-adopters. The two objective food security measures both decrease in age and size of the household for adopters. The negative correlation of age with food security implies that younger farmers are more productive and therefore more food secure than older ones, which is in line with findings by Alene and Manyong (2006). The significant and negative sign on the household size may suggest that with an increase in the number of people, there is competition for both food and financial resources, especially in cases where the members are not very productive. As expected, education of the household, total land cultivated per capita, kinship, off-farm income and rainfall index have a positive impact on food security. The distance to the extension agent's

[17] The results for the breakeven food security and occasional food insecurity are not presented to conserve space but are available on request. We also tried to estimate the model for chronic food insecurity; however it did not converge probably because of the small number of chronically food insecure households.

office and output market reduces the subjective food security measure only for adopters. The implication is that with an increase in distance to output, transport costs also increase and this reduces the profits for farmers. In most cases, farmers are forced to sell their produce to unscrupulous buyers within the villages at a low, unprofitable price as opposed to traveling long distances to better markets. Generally, the results show that household food security is affected by a number of socioeconomic, social capita and location variables, which in some cases have a different effect for adopters and non-adopters.

Table 4.6 also presents the balancing test after propensity score reweighting. The results show that we cannot reject the null hypothesis that the covariates are balanced implying that there is no evidence that the covariates used remain imbalanced after propensity score reweighting. This implies that we can proceed and estimate the ATTs for our outcome variables.

Table 4.6: Inverse-probability-weighted regression adjustment estimates for the determinants of food security

	Ln (Per capita food expenditure)		Objective food security dummy		Subjective food security dummy	
Explanatory variables	Adopters	Non-adopters	Adopters	Non-adopters	Adopters	Non-adopters
Age of household head	-0.02 (0.00)***	-0.01 (0.01)	-0.01 (0.00)**	-0.01 (0.01)	0.00 (0.00)	0.00 (0.01)
Gender of household head	-0.03 (0.11)	0.02 (0.22)	0.09 (0.13)	0.20 (0.23)	-0.04 (0.14)	-0.23 (0.25)
Education of household head	0.01 (0.02)	0.08 (0.03)**	0.04 (0.02)**	0.04 (0.03)	0.03 (0.02)*	0.09 (0.04)
Household size	-0.08 (0.02)***	-0.06 (0.04)	-0.08 (0.02)***	-0.07 (0.04)	0.01 (0.02)	0.05 (0.04)
Dependency ratio	-0.19 (0.08)**	0.07 (0.09)	-0.16 (0.08)**	0.12 (0.12)	0.12 (0.09)	-0.18 (0.15)
Kinship	-0.05 (0.03)**	0.04 (0.01)***	-0.01 (0.01)	0.07 (0.03)**	-0.01 (0.01)	0.03 (0.02)***
Credit	-0.01 (0.13)	-0.21 (0.23)	-0.05 (0.14)	-0.16 (0.27)	-0.32 (0.15)**	0.25 (0.29)
Land per capita	-0.16 (0.21)	0.74 (0.31)**	0.25 (0.13)*	0.75 (0.28)**	0.30 (0.14)**	0.41 (0.31)
Ln off-farm income	0.02 (0.01)**	0.02 (0.01)	0.02 (0.01)***	0.04 (0.02)**	-0.01 (0.01)	0.00 (0.02)
TLU	0.03 (0.01)**	0.02 (0.02)	0.01 (0.02)	-0.04 (0.03)	0.04 (0.02)**	-0.10 (0.03)**
Safety nets	0.12 (0.12)	-0.06 (0.2)	0.15 (0.14)	-0.26 (0.24)	-0.11 (0.15)	1.15 (0.27)***
Market information	-0.27 (0.15)*	0.68 (0.19)***	-0.13 (0.14)	0.42 (0.22)**	0.26 (0.15)*	0.02 (0.22)
Contacts	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.01 (0.00)*	0.00 (0.00)	0.02 (0.01)**
Rainfall index	0.30 (0.11)**	0.42 (0.20)**	0.33 (0.13)**	0.42 (0.24)*	0.01(0.14)	0.63 (0.24)**
Ln Distance to extension office	0.02 (0.06)	-0.22 (0.14)	0.00 (0.05)	-0.14 (0.10)	-0.16 (0.06)**	-0.10 (0.1)
Ln Distance to village market	0.07 (0.04)	-0.10 (0.06)	0.02 (0.04)	-0.04 (0.06)	-0.11 (0.04)**	-0.03 (0.07)
Lundazi district	0.27 (0.15)*	-0.20 (0.22)	0.14 (0.13)	-0.74 (0.27)**	-0.1 (0.14)	-0.35 (0.26)
Katete district	0.09 (0.15)	-0.08 (0.26)	0.18 (0.18)	-0.02 (0.27)	0.3 (0.2)	1.34 (0.34)***
Constant	14.22 (0.43)***	12.97 (0.69)***	0.45 (0.44)	-0.07 (0.87)	0.94 (0.48)**	-1.41 (0.94)
Balancing test after propensity score reweighting						
Over identification test for covariate balance	$\chi^2 = 21.50$; $P > \chi^2 = 0.31$					

*, **, and *** denotes significance level at 10%, 5% and 1% (Robust standard errors in parentheses).

4.5.3 Average treatment effects using Inverse-Probability-Weighted Regression Adjustment (IPWRA)

Results[18] on the impact of improved maize adoption on six outcome variables— per capita food expenditure (ln) objective food security, subjective food security, food surplus, breakeven food security and occasional food insecurity—are presented in table 4.7.

Table 4.7: Average treatment effects using inverse-probability-weighted regression adjustment (IPWRA) Model

Outcome variables	Adoption status		Average treatment effect
	Adopters	Non-adopters	ATT
Per capita food expenditure (ZMK' 000)	585	460	127 (0.13)*
Objective food security dummy	0.58	0.37	0.21 (0.04)***
Subjective food security dummy	0.78	0.70	0.08 (0.04)***
Food surplus	0.58	0.48	0.10 (0.04)**
Breakeven food security	0.20	0.23	-0.03 (0.04)
Occasional food insecurity	0.19	0.19	-0.00 (0.03)

*, **, and *** denotes significance level at 10%, 5% and 1% (Robust standard errors in parentheses).
Note: The results for chronic food insecurity are not presented because the observations were very few, hence the model did not converge.

The results show that generally, adopters were better off than non-adopters on all the outcome variables. Adoption of improved maize has a significant and positive impact on the per capita food expenditure and the probability of being food secure. The added contribution of adopting improved maize varieties towards per capita food expenditure was estimated at ZMK127,000 (US$24). In other words, the per capita food expenditure of adopters that can be attributed solely to adoption of improved maize varieties was 28% higher than that of the non-adopters. The results imply that improved maize adoption increases the food expenditure by almost a third as compared to non-adopting households, after controlling for the observed heterogeneity of household, social capital and locational characteristics. On average, the probability of being food secure is 21% higher for adopting households than non-adopting households when we consider the objective food security dummy. Similarly the subjective food security measure shows that improved maize adoption increases the probability of being food secure on average by 8% among adopting households. The results also show that adopting households had a higher probability of having a food surplus (10%) as compared to non-adopting households (table 4.7).

[18] Before specifying the full model, we first estimated a parsimonious model (with only the adoption dummy and the district dummies). The estimates were quite stable, also after specifying the full model.

The results generally show that objective measures resulted in higher impacts as compared to the subjective measures and one of the reasons for this may be the measurement of food expenditure. The food expenditure data is based on a one season survey data and hence this may result in either over or under reporting the real status of household food security (Shiferaw *et al.*, 2014).

4.5.4 Propensity score matching and Rosenbaum bounds on treatment effects

As a robustness check, we compare our IPWRA results with results from standard propensity score matching (PSM). Therefore, results presented in table 4.4 were used in matching adopters and non-adopters. The PSM approach produces very similar results to the estimates in table 4.7. Results in table 4.8 show that the adoption of improved maize increases the expenditure on food by adopting households by an average of ZMK225,000 (US$43) or 63% more than non-adopting households. Similarly, probability of food security increases by 8% to 23% with improved maize adoption. The PSM results also reveal that adoption of improved maize varieties reduces the chances of household experiencing occasional food insecurity by 7%.

Table 4.8: Average treatment effects using propensity score matching

Outcome variables	Kernel Based Matching (KBM)[a]		Average treatment effect
	Adopters	Non-adopters	ATT
Per capita food expenditure (ZMK`000)	580	355	225 (0.12)***
Objective food security dummy	0.58	0.35	0.23 (0.04)***
Subjective food security dummy	0.78	0.70	0.08 (0.03)**
Food surplus	0.58	0.44	0.13 (0.04)**
Breakeven food security	0.20	0.26	-0.05 (0.03)
Occasional food insecurity	0.19	0.26	-0.07 (0.03)**

** and *** denotes significance level at 5% and 1% (Standard errors in parentheses).
[a] We use Epanechnikov kernel and band width 0.3.

The estimation of treatment effects with PSM is based on the CIA; therefore if adopters and non-adopters differ on unobserved variables which simultaneously affect assignment into treatment and the outcome variable, a hidden bias may arise. To check whether the PSM results are sensitive to hidden bias due to unobserved factors, we apply the bounding approach proposed by Rosenbaum (2002), which determines how strongly an unobserved factor may influence the selection process in order to invalidate the results of PSM analysis (Caliendo *et al.*, 2008). Specifically, we use the Mantel-Haenszel (MH) bound for binary outcomes suggested by Aakvik (2001) and the Hodges-Lehman (HL) bound for continuous outcomes, as recommended by

DiPrete and Gangl (2004). Rosenbaum's method of sensitivity analysis relies on the sensitivity parameter (gamma or log-odds ratio) that measures the degree of departure from a PSM analysis that is free of hidden bias (Caliendo *et al.*, 2008). We consider several critical values of gamma ranging from one to two. If gamma is one, it implies that there is no effect of unobservables on food security while an odds ratio of two implies that due to unobservables, a farmer is two times more likely to be food secure if he/she is an adopter of improved maize than another farmer with similar observable characteristics.

Table 4.9: Rosenbaum bounds for treatments effects of improved maize varieties on food security

Outcome variables	Gamma	Q_hl+	Q_hl-	p+	p-
Ln (Per capita food expenditure)	1.00	0.50	0.50	0.00	0.00
	1.20	0.42	0.59	0.00	0.00
	1.40	0.35	0.66	0.00	0.00
	1.60	0.29	0.72	0.00	0.00
	1.80	0.24	0.77	0.00	0.00
	2.00	0.19	0.82	0.00	0.00
Objective food security	1.00	6.89	6.89	0.00	0.00
	1.20	5.66	8.14	0.00	0.00
	1.40	4.62	9.22	0.00	0.00
	1.60	3.74	10.16	0.00	0.00
	1.80	2.96	11.01	0.00	0.00
	2.00	2.26	11.77	0.01	0.00
Subjective food security	1.00	2.75	2.75	0.00	0.00
	1.20	1.64	3.87	0.05	0.00
	1.40	0.70	4.84	0.24	0.00
	1.60	-0.05	5.68	0.52	0.00
	1.80	0.66	6.44	0.25	0.00
	2.00	1.30	7.13	0.10	0.00
Food surplus	1.00	4.58	4.58	0.00	0.00
	1.20	3.34	5.84	0.00	0.00
	1.40	2.30	6.92	0.01	0.00
	1.60	1.39	7.86	0.08	0.00
	1.80	0.60	8.69	0.27	0.00
	2.00	-0.04	9.45	0.52	0.00
Occasional food insecurity	1.00	2.48	2.48	0.01	0.01
	1.20	3.55	1.43	0.00	0.08
	1.40	4.46	0.55	0.00	0.29
	1.60	5.26	0.05	0.00	0.48
	1.80	5.98	0.72	0.00	0.24
	2.00	6.64	1.33	0.00	0.09

Notes: N= 810. Gamma is the log odds differential assignment due to unobserved factors. In the case of the continuous outcome variable (Ln Food expenditure per capita), (the upper and lower bounds are Hodges-Lehmann point estimates. For the binary outcome variables (objective and subjective food security), the upper and lower bounds are Mantel-Haenszel point estimates. The results presented are only for significant variables.

The finding of a positive effect of improved maize adoption on the objective household food security (both food expenditure and the food security dummy) is the most robust to presence of selection bias (table 4.9). The positive effect of adoption on objective food security is not sensitive to selection bias due to unobserved variables, even if we allow adopters and non-adopters to differ by as much as 100% in terms of unobserved covariates. On the other hand, the critical level of gamma at which the conclusion of a positive impact of improved maize adoption on subjective food security is questioned starts at 1.4. The critical level of gamma = 1.4 implies that adopters and non-adopters differ by a factor of 1.4 (40%) in terms of unobserved covariates. The results for the other variables can be interpreted in a similar way. These values are large given that we used a rich set of variables that affect both the adoption decision and the outcome variable. Caliendo *et al.* (2008) mention that these values or bounds reflect "worst-case scenarios" and hence do not indicate the presence of selection bias but only tell us how strong the selection bias should be to invalidate our conclusions. We therefore conclude that the results in tables 4.7 and 4.8 are robust to unobserved characteristics.

4.6 Conclusions and policy implications

This chapter examined the impact of improved maize varieties on household food security in eastern Zambia using farm household survey data collected in 2012. The chapter employed an inverse probability weighted regression approach that produces estimates that are doubly robust against selection bias, complemented with results from more common propensity score matching.

The empirical results from all the estimation methods used in this chapter are largely consistent and indicate that improved maize technology adoption has had a significant positive impact on food security in Zambia. The average treatment affects estimates from the IPWRA method show per capita food expenditure and the probability of food security increase by ZMK127,000 (US$24) and 21% with improved maize adoption, respectively. Results from the PSM show similar results. Sensitivity analysis using Rosenbaum bounds on treatment effects show that the impacts are quite robust against hidden bias due to potential unobserved factors.

Compared with other impact assessment methods often used in the literature and also presented in this chapter, the IPWRA method is efficient in accounting for observed heterogeneity as shown by the similar estimates obtained under the other approaches presented in this chapter. This method can easily be adapted to other cases where policy makers wish to have information on, for instance the differential impact of adoption on adopters and non-adopters of new agricultural technologies. The major advantage of IPWRA is however its robustness to unobserved heterogeneity, a problem that often affects impact assessments.

This chapter also shows that it is important to employ multiple measures of food security in order to understand the impact of modern agricultural innovations on food security. Both subjective and objective measures of food security are useful in explaining the impact of improved maize adoption. Although the FAO (2009) suggests the use of more objective measures of food security such as food expenditure, Shiferaw *et al.* (2014) show that combining both objective and subjective measure measures of food security provides more robust evidence of the impact of improved crop varieties. Similarly although subjective measures maybe questionable, it is advisable to use these measures as a supplement to objective measures and not as substitute (Ravallion and Lokshin, 2002). Moreover, in recent years policy-makers and programme implementers have been seeking measurement techniques for food security that are simple to use and easy to analyse. Data related to subjective food security measures are quite easy to obtain and may be used in situations where data collection on food expenditure is not feasible. Therefore, this chapter advocates the use of both objective and subjective measures in order to have a more informed understanding of the impact of agricultural technologies on food security.

Maize, being the most important food staple in Zambia has a great bearing on the food security status of farm households. It is therefore imperative that an environment that is conducive is created that promotes the adoption of maize yield improving technologies. Although this chapter largely concentrated on disentangling the impacts of improved maize varieties on food security, it also showed that education and access to information are important determinants of both improved maize adoption and food security. Hence investing in education may help farmers understand the importance of growing these varieties which in the long run can encourage their adoption. In addition, strengthening the national extension system can also help in providing relevant information relating to these varieties which in turn can help farmers make informed choices.

CHAPTER 5

DETERMINANTS OF CHILD NUTRITIONAL STATUS IN THE EASTERN PROVINCE OF ZAMBIA: THE ROLE OF IMPROVED MAIZE VARIETIES[19]

Abstract

Using household survey data from a sample of 810 households, this chapter analyses the determinants of children's nutritional status and evaluates the impacts of improved maize varieties on child malnutrition in eastern Zambia. The chapter uses an endogenous switching regression technique, combined with propensity score matching to assess the determinants of child malnutrition and impacts of improved maize varieties on nutritional status. The study finds that child nutrition worsens with the age of the child and improves with education of household head and female household members, number of adult females in the household, and access to better sanitation. The study also finds a robust and significant impact of improved maize varieties on child malnutrition. The empirical results indicate that adoption of improved maize varieties reduces the probability of stunting by an average of about 26 %.

Key words: children's nutritional status, stunting, endogenous switching probit, Zambia.

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5.1 Introduction

Malnutrition remains pervasive in many countries despite significant reductions in income poverty in recent years (Horton *et al.,* 2008). More than 30% of the developing world's population suffers from micronutrient deficiencies and approximately one-third of the children in developing countries are either underweight or stunted (World Bank, 2008). Malnutrition is the largest single factor contributing to the global problem of disease and accounts for about 30% of infant deaths (Headey, 2013b). Malnutrition also has adverse effects on the child's physical development, mental capacity, school performance, and reduces adult labour productivity and wage earnings, as well as overall economic growth (Apodaca, 2008; Horton *et al.,* 2008).

Malnutrition is widespread among children in Zambia and it is one of the leading contributors to the high burden of disease in the country (Masiye *et al.,* 2010). According to the UNDP (2011), about 50% of children under the age of five are stunted or too short for their age indicating chronic malnutrition, while about 19% of Zambian children are underweight or too thin for their age.

Malnutrition principally results from the independent or combined effects of three elements: inadequate food availability, poor access to food by the hungry and poor food utilization (Staatz, 2000). Food availability refers to the supply of food through adequate production (commercial and home produced), food aid, or food imports (Apodaca, 2008). Food access on the other hand refers to whether a person has a socially recognized claim on the available supply of food. It follows therefore that owning productive assets for producing food and income both play a role in enabling people to have access to food. Food utilization depends on having adequate knowledge about how to prepare food in a way that preserves its nutritional value and to get it to those in the household who need it most.

The above implies that adoption of improved agricultural technologies can play an important role in reducing malnutrition. Adoption of modern agricultural technologies such as improved maize varieties has a positive and significant impact on crop yields as well as household welfare (Alene *et al.,* 2009; Becerril and Abdulai, 2010). Increased agricultural production through adoption of improved maize varieties increases the income earning opportunities for most poor households in rural areas, thereby improving access to food. According to Headey (2013), higher incomes raise expenditure levels on food, thereby increasing the quality and quantity of diets. Furthermore, income raises expenditure on nutrition-relevant non-food expenditures, such as health, sanitation, electricity, water, and housing quality.

The purpose of this chapter is to analyse the determinants of chronic malnutrition (stunting) and to evaluate the impacts of improved maize varieties on stunting in eastern Zambia. The chapter uses household survey data from a sample of 810 households and applies the endogenous switching probit (ESP) model to identify the determinants of child nutritional status and impact of improved maize varieties. We complement our results by also estimating the impacts of improved maize using a semi-parametric propensity score matching (PSM).

The chapter adds to existing literature on child nutrition and the nutritional impacts of improved agricultural technologies on malnutrition. A number of studies have looked at the determinants of child malnutrition in Africa (e.g. Christiaensen and Alderman, 2004; Kabubo-Mariara *et al.*, 2008; Masiye *et al.*, 2010; Ssewanyana 2003; Asenso-Okyere *et al.*, 1997). However, to our knowledge, none of the studies have tried to establish a causal link between improved agricultural technologies such as improved maize varieties and child malnutrition using rigorous impact evaluation methods except Zeng *et al.* (2014). They use Instrumental Variable (IV) methods to show that adoption of improved maize varieties improves the nutritional status of children in Ethiopia. One of the drawbacks of most IV methods is that they only assume an intercept effect which may under- or over-estimate the impacts of adoption. Zeng *et al.* (2014) also assumed that the characteristics and resources of adopters and non-adopters have the same impact on outcome variables (i.e., homogenous returns to their characteristics and resources). In this study, we control for selection and endogeneity bias that may potentially arise due to correlation between unobserved household characteristics and observed health outcomes using the ESP approach. The ESP model estimates two separate equations for adopters and non-adopters, thus allowing us to explore the differential effects of the two groups.

The remainder of the chapter is organized as follows. The next section discusses child malnutrition in Zambia. The third section outlines the conceptual and empirical frameworks followed by a section presenting the data and descriptive statistics. Section 5.5 presents the empirical results and conclusions are drawn in the last section.

5. 2 Child Malnutrition and adoption of improved maize varieties in Zambia

5.2.1 Child malnutrition in Zambia

Child malnutrition rates in Zambia have long been high, but there has been a noticeable increase in the past decade. Although the burden of other infectious and preventable diseases is high and contributes significantly to child morbidity and mortality, nearly 52% of all under 5 deaths in Zambia are attributed to malnutrition (UNICEF, 2008). There are several factors that have been identified as causes of child malnutrition in Zambia, including household food insecurity, lack of access to health and other social services, especially among the poor and rural population, poor nutrition of mothers and frequent infections (Masiye *et al.,* 2010; Sitko *et al.,* 2011). Poverty coupled with current rising food and fuel prices, scarcity of food due to extensive crop loss owing to climate change effects such as flooding, and in some cases lack of knowledge on proper infant feeding practices further exacerbates the underlying chronic nutrition problems (UNICEF, 2008).

Table 5.1: Trend in the malnutrition levels of under-five children in Zambia, 1992-2009 (%)

Indicator	1992 (ZDHS)	1996 (ZDHS)	2002 (ZDHS)	2007 (ZDHS)	2009 (ZHDR)
Stunting	46	49	53	45	50
Wasting	6	5	6	5	-
Underweight	21	19	23	15	19

Note: ZDHS=Zambia Demographic Health Survey; ZHDR= Zambia Human Development Report.
Source*:* UNZA, CSO and MII (1993, 2009), CSO, CBoH and ORC Macro (2003), UNDP (2011).

Table 5.1 presents trends in the nutritional status of children in Zambia using anthropometric data from the Zambia Demographic Health Surveys (ZDHS) undertaken from 1992-2007 and the 2011 Zambia Human Development Report (ZHDR). Inspection of table 5.1 shows that there was no consistent trend in the nutritional indices for children under the age of five over the past four ZHDS surveys (1992, 1996, 2002, and 2007). Wasting remained at roughly the same levels throughout. During the period between 1992 and 2002, Zambia experienced an increasing trend in the malnutrition levels as measured by stunting and underweight, coinciding with the time that the country experienced some droughts and unfavourable weather. However, the results of the 2007 ZDHS show a notable improvement in the nutritional status of children as measured by both the height-for-age and weight-for-age indices from the 2002 and 2007 ZDHS surveys. Although there was a significant reduction in stunting (45%) and underweight (15%) levels from 2002 to 2007, the stunting rates were still high relative to the average prevalence of child stunting of 39% for 19 sub-Saharan African countries in the mid-nineties (Morrisson *et al.*, 2002). The 2007 ZDHS further reveals that there were slightly more boys (48%) than girls (42%) who were stunted. Results from all the demographic health surveys show that the rural areas have more children who are suffering from malnutrition than those in urban areas. Among the nine provinces, Eastern province has one of the highest rates of malnutrition in Zambia at 50%, third only to Central and Luapula provinces at 53% and 59%, respectively. Table 5.1 further shows that the 2009 average stunting and underweight rates have started rising again, with stunting going up from 45% to 50% and underweight going up from 15% to 19%.

5.2.2 Adoption of improved maize varieties in Zambia

Improved maize varieties were introduced to smallholder farmers in Zambia in the 1970s and almost 60% of the farmers have adopted these varieties to date (Kumar, 1994; Tembo and Sitko, 2013). Improved maize varieties consist of both hybrids and open pollinated varieties (OPVs). In simple terms, hybrid maize results from the fertilization of one maize plant by another genetically un-related plant (MacRobert *et al.,* 2014), while OPVs are populations that breeders have selected for a very specific set of traits and generally they can be replanted up to three years without a decline in yields (Becerril and Abdulai, 2010). Over the past three decades, more than 50 improved maize varieties have been developed by the Zambia Agricultural Research Institute (ZARI) in collaboration with the International Maize and Wheat Improvement Center (CIMMYT) and International Institute of Tropical Agriculture (IITA) (Kalinda *et al.*, 2014). The Eastern province of Zambia is one of the largest producers of maize in the country. For instance in the 2011-2012 season, the province accounted for 21% of the total maize produced by small and medium scale farmers in Zambia (Tembo and Sitko, 2013), second only to the Southern province which contributed about 22%.

Improved maize varieties have several advantages over local varieties which include, but are not limited to; higher yields, early maturation, uniform grain color and resistance to diseases. Most of the improved varieties in Zambia have an estimated yield advantage of 20-60% over locals (Howard and Mungoma, 1996). For instance one of the most popular varieties in the Eastern province of Zambia is MRI 634, which was released in 2000 through the Zambia Agricultural Research Institute (ZARI). This is a medium maturing hybrid variety, with dent white grains and a potential yield of 10 tons per ha. Increased maize yields certainly play an important role in increasing incomes and reducing poverty through the sale of surplus maize. For example, recent studies in Zambia show that improved maize varieties have significantly increased income for adopters (Khonje *et al.,* 2015; Smale and Mason, 2014). Although there is enough evidence on the productivity and income effects of improved maize varieties, there is limited evidence on the nutritional impacts on children under the age of five.

5.3 Theoretical and empirical approaches

5.3.1 Theoretical framework

Figure 5.1 shows the pathway through which agriculture is expected to affect child nutritional status. The figure shows that there are two pathways through which adoption of improved maize varieties could affect child nutritional status. It is expected that improved maize adoption will lead to an increase in yields and consequently availability of more food for the household. On the other hand, improved maize adoption is expected to increase household income through the sale of surplus maize, which in turn translates into increased food expenditure on high calorie and protein foods, finally leading to improvement in child nutritional status (solid arrows in figure 5.1).

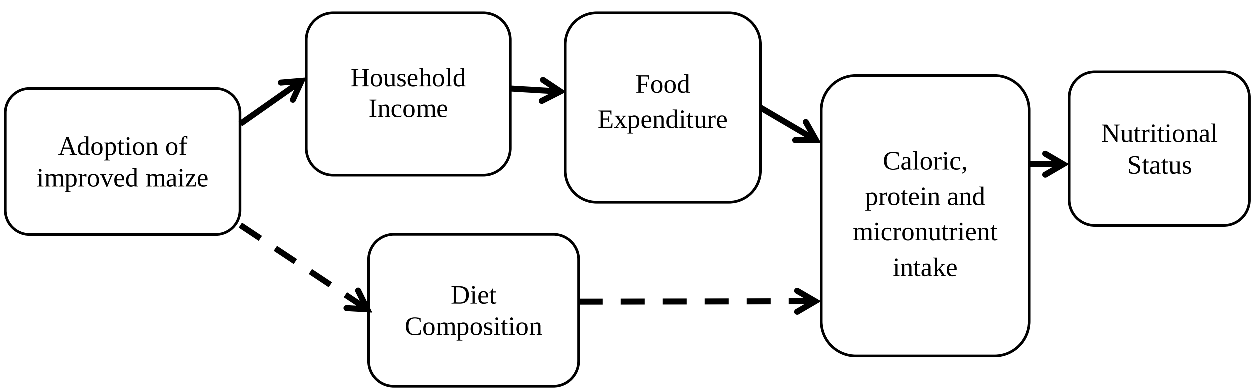

Figure 5.1: Pathways of impact of agricultural interventions on child nutritional status (adapted from Masset *et al.* (2011)).

The other pathway involves the adoption of nutrition enhancing technologies, e.g. adoption of crops that are high in protein content. Consumption of such crops is expected to increase the intake of proteins which will translate into improved child nutritional status. In this study, we envisage that adoption of improved maize varieties will affect child nutritional status through both the household income pathway and the diet composition pathway. According to Dorosh *et al.* (2009) maize accounts for about 60% of the national calorie consumption and serves as the dietary mainstay in central, southern, and eastern Zambia, hence in addition to income, we believe that adoption of improved maize varieties also serves as a proxy for food availability, providing the much needed calories and energy for children. The supply of child nutrition is a complex process, and it may involve multiple relationships, hence we cannot entirely rule out the nutrition effects through the diet composition pathway.

The challenge in this study is to estimate the causal effect of improved maize adoption on child nutrition (figure 5.1). One way is to compare the stunting levels for children from improved maize adopting and non-adopting households. However, just comparing stunting levels between adopters and non-adopters may be misleading, because there may also be differences in e.g. access to resources, sanitation and health services. Without controlling for these other factors the conclusions obtained from this type of analysis may be false. One way to control for other factors would be to regress the adoption variable on the outcome variable (stunting) with variables such as access to sanitation added as controls. However, because farmers often self-select into the adopter category or some technologies are targeted to a given group of farmers, endogeneity problems may arise which may lead to biased estimates (Alene and Manyong, 2007; Rao and Qaim, 2011). Other methods such as instrumental variable (IV) regression can be used to account for endogeneity; however this method assumes technology adoption has an average impact on child nutrition over the entire sample of children, by way of an intercept shift in the child nutrition production function. Other factors such as education can also lead to an improvement in child nutrition by way of slope shifts in the nutrition production function but are not captured by IV type of regressions. To fully assess the differential effects of the above aspects, two separate equations for adopters and non-adopters have to be specified (Alene and Manyong, 2007). Interactions between improved maize adoption and a set of explanatory variables at the same time accounting for endogeneity can only be effectively examined through the simultaneous endogenous switching regression model.

5.3.2 The endogenous switching probit model

The modelling of the impact of adopting improved maize varieties on child nutritional status using the ESP model proceeds in two stages. The first stage is the decision to adopt improved maize varieties and it is estimated using a probit model. In the second stage a probit regression with selectivity correction is used to examine the relationship between the outcome variable (stunting) and a set of explanatory variables conditional on the adoption decision.

The observed outcome of the improved maize varieties adoption decision can be modelled in a random utility framework. Following Aakvik *et al.* (2000), Heckman *et al.* (2001) and Alene and Manyong (2007) let the adoption of the improved maize varieties be a binary choice, where a farmer decides to adopt improved maize varieties if the difference between the utility of adopting and not adopting improved maize varieties is positive. Let this difference be denoted as $I^* = U_1 - U_0$, where U_1 is the utility obtained from adopting improved maize varieties and U_0 the utility from not adopting improved maize varieties. The farmer will adopt improved maize varieties if $I^* > 0$. However, I^* is not observed, what is observed is I, a binary indicator that equals one if a farmer adopts improved and zero otherwise. More formally, the relationship can be expressed as:

$$I_i^* = Z'\alpha + \varepsilon_i$$
$$I_i = 1 \; if \; I_i^* > 0,$$
$$I_i = 0 \; if \; I_i^* \leq 0. \tag{1}$$

where Z is a vector of observed household and farm characteristics determining adoption; α is the vector of unknown parameters to be estimated; and ε_i the vector of random disturbances related with the adoption of improved maize varieties with mean zero and variance σ_i^2.

Following Lokshin and Sajaia (2011) the two outcome regressions equations, conditional on adoption can be expressed as:

Regime 1 (Adopters): $y_{1i} = \beta_1 X_{1i} + u_{1i}$ if $I_i = 1$
Regime 2 (Non-adopters): $y_{2i} = \beta_2 X_{2i} + u_{2i}$ if $I_i = 0$ (2)

where y_{1i} and y_{2i} both represent our outcome variable, viz. stunting; X_{1i} and X_{2i} are vectors of weakly exogenous covariates; β_1 and β_2 are vectors of parameters; and u_{1i} and u_{2i} are random disturbance terms.

For the ESP model to be identified, it is important for the Z variables in the adoption model (equation 1) to contain a selection instrument. We use distance to extension office (minutes) and sources of improved variety information (government extension (1 = yes) and non-governmental organization extension (1 = yes)) as instrumental variables for the identification of the impact of adoption on child nutrition. We envisage that farmers are less likely to adopt improved maize varieties if they live far from the office of the extension agents because the further away, the more costs are incurred if the farmers are to access extension. Similarly, information variables affect the decisions to adopt improved agricultural technologies in Africa (Di Falco and Veronesi, 2013; Di Falco *et al*,. 2011). We envisage that these variables are correlated with the adoption of improved maize varieties, but are unlikely to directly affect the nutritional status of children. We follow Di Falco *et al.* (2011) in establishing the admissibility of these instruments; The results[20] show that these three variables can be considered as valid instruments because they are jointly statistically significant in explaining the adoption decision [$\chi2$ = 13.17 (p = 0.004)] but are not statistically significant in explaining the outcome equation [$\chi2$ = 5.61 (p = 0.133)].

The estimation of β_1 and β_2 above using a probit regression may lead to biased estimates because of self-selection into the adopter or non-adopter categories resulting from the non-zero covariance between the error terms of the adoption decision equation and the outcome equation (Abdulai and Huffman 2014). The error terms (u_1, u_2, ε) are assumed to have a joint normal distribution with mean vector zero and correlation matrix;

$$\Omega = \begin{bmatrix} 1 & \rho_0 & \rho_1 \\ & 1 & \rho_{10} \\ & & 1 \end{bmatrix} \tag{3}$$

Where ρ_0 and ρ_1 are the correlations between the error terms u_1 , ε_i and u_2, ε_i and ρ_{10} is the correlation between of u_1 and u_i . We assume that ρ_{10}=1, since α in equation 1 is estimable only up to a scalar factor.

5.3.3 Estimation of average treatment effects

The endogenous switching probit model can be used to estimate the average treatment effects on the treated (ATT) and the average treatment effect of the untreated (ATU) by comparing the expected values of the outcomes of adopters and non-adopters in actual and counterfactual

[20] Since the treatment and outcome variables are both binary, we used a probit regression model to test validity of the instrumental variables. The results from these tests are not discussed because of limited space but are available on request.

scenarios. Following Aakvik *et al.* (2000) and Lokshin and Sajaia (2011) we calculated the ATT and ATU based on the expected outcomes, conditional on adoption as:

Adopters with adoption (actual expectations observed in the sample)

$$E(y_{1i}|I = 1; X) \tag{4a}$$

Non-adopters without adoption (actual expectations observed in the sample)

$$E(y_{2i}|I = 0; X) \tag{4b}$$

Adopters had they decided not to adopt (counterfactual expected outcome)

$$E(y_{2i}|I = 1; X) \tag{4c}$$

Non-adopters had they decided to adopt (counterfactual expected outcome)

$$E(y_{1i}|I = 0; X) \tag{4d}$$

The average treatment effect on the treated (ATT) is computed as the difference between (4a) and (4c);

$$ATT = E(y_{1i}|I = 1; X) - E(y_{2i}|I = 1; X) \tag{5}$$

The average treatment effect on the untreated (ATU) is given by the difference between (4d) and (4b)

$$ATU = E(y_{1i}|I = 0; X) - E(y_{2i}|I = 0; X) \tag{6}$$

Previous studies that have used the ESP model include; (Ayuya *et al.*, 2015; Gregory and Coleman-Jensen, 2013; Lokshin and Glinskaya, 2009).

5.3.4 The propensity score model

The ESP model can sometimes be sensitive to exclusion restriction assumptions, hence to check the robustness of the ESP results; we also estimated the ATT using the propensity score matching approach.

Following Becerril and Abdulai (2010) and Caliendo and Kopeinig (2008), let Y_{iA} and Y_{iN} denote child stunting in household *i* that adopts an improved variety and the household that does not adopt an improved variety, respectively. In reality, only Y_{iA} or Y_{iN} is observed at one particular time and not both. Let T represent a binary treatment variable that equals one if a farmer adopts an improved variety and zero otherwise. The observed stunting can be expressed as:

$$Y_i = T_i Y_{iA} + (1 - T_i) Y_{iN} \quad T = (0,1) \tag{7}$$

Furthermore, let P be the probability of observing a household with $T = 1$. The Average Treatment Effect (ATE) can be expressed as follows:

$$ATE = P \cdot [E(Y_A|T = 1) - E(Y_N|T = 1)] + (1 - P) \cdot [E(Y_N|T = 0) - E(Y_N|T = 0)] \tag{8}$$

The ATE is the weighted average effect of adoption on the population, which is simply the difference of the expected outcomes after adoption and non-adoption (Caliendo and Kopeinig, 2008). However since the counterfactual mean $E(Y_N|T = 1)$ is not observed, one has to choose a proper substitute for it in order to estimate ATT (Caliendo and Kopeinig, 2008). According to Caliendo and Kopeinig (2008), using the mean outcome of untreated individuals $E(Y_N|T = 0)$ in non-experimental studies is usually not a good idea because it is most likely that components which determine the treatment decision also determine the outcome variable of interest. To address this problem, the Propensity Score Matching (PSM) approach is used. The propensity score is defined as the conditional probability that a farmer adopts the new technology, given pre-adoption characteristics (Rosenbaum and Rubin, 1983). The PSM employs the unconfoundedness assumption also known as conditional independence assumption (CIA) or selection on observables assumption. This assumption implies that systematic differences in outcomes between adopters and comparison individuals with same values for covariates are attributable to adoption thereby making adoption random and uncorrelated with the outcome variables (Ali and Abdulai, 2010; Caliendo and Kopeinig, 2008). The propensity score can be expressed as:

$$p(X) = \Pr(T = 1|X) = E(T|X); \;\; p(X) = F\{h(X_i)\}, \tag{9}$$

where X is the multidimensional vector of pre-treatment characteristics (same as Z in equation 1 above); and F {.} is the cumulative distribution function. If the $p(X)$ is known, then the ATT can be estimated as follows:

$$\begin{aligned} ATT &= E\{Y_{iA} - Y_{iN}|T = 1\} \\ &= E[E\{Y_{iA} - Y_{iN}|T = 1, p(X)\}] \\ &= E[E\{Y_{iA}|T = 1, p(X)\} - E\{Y_{iN}|T = 0, p(X)\}|T = 1] \end{aligned} \tag{10}$$

where the outer expectation is over the distribution of ($p(X)$ $|T = 1$) and Y_{iA} and Y_{iN} are the potential outcomes in the two counterfactual situations of adoption and no adoption respectively.

5.4. Data, variable specification and descriptive statistics

5.4.1 Survey design and data collection

The data used in this chapter come from a survey of 810 sample households conducted in January and February 2012 in eastern province of Zambia. This was a baseline[21] survey conducted by the International Institute of Tropical Agriculture (IITA) and the International Maize and Wheat Improvement Centre (CIMMYT) in collaboration with the Zambia Agricultural Research Institute (ZARI) for the project entitled Sustainable Intensification of Maize-Legume Systems for the eastern province of Zambia (SIMLEZA). A survey questionnaire was prepared and administered by trained enumerators who collected data from households through personal interviews. The survey was conducted in the same SIMLEZA project districts in eastern Zambia—Chipata, Katete, and Lundazi—which were targeted by the project as the major maize and legume growing areas. In the first stage, each district was stratified into agricultural blocks[22] (8 in Chipata, 5 in Katete and 5 in Lundazi) as primary sampling units. In the second stage, 41 agricultural camps were randomly selected, with the camps allocated proportionally to the selected blocks and the camps selected with probability of selection proportional to size. Overall, 17 camps were selected in Chipata, 9 in Katete and 15 in Lundazi. A total sample of 810 households was selected randomly from the three districts with the number of households from each selected camp being proportional to the size of the camp (table 5.2).

Table 5.2: Distribution of sample households by district and gender

District	Number of blocks	Number of camps	Female-headed	Male-headed	All
Chipata	8	17	129	205	334
Katete	5	9	63	117	180
Lundazi	5	14	98	198	296
All	18	40	290	520	810

[21] A follow up survey will be conducted in 2015 where the same household who were interviewed at baseline will be interviewed.

[22] A camp is a catchment area made up of 8 different zones consisting of villages and is headed by an agricultural camp officer. A block is made up of camps and is managed by an agricultural block officer.

The selected sample of 810 households was surveyed using a semi-structured questionnaire Of the 810 households, 444 households provided anthropometric data on 752 children of ages 3–60 months. The weight of the children was measured using a standard scale. The standing height as opposed to recumbent length was measured using a measuring ruler, preferred mainly for ease of use. Table 5.3 shows the total number of 670 children who were considered in the analysis since extreme or biologically implausible z-scores were removed as recommended by Masiye *et al.* (2010). The extreme values for height-for-age z-scores (HAZ) were those which were below -6 or above 6.

Table 5.3: Distribution of sample children by district and gender

District	Gender of Child		All
	Female	Male	
Chipata	140	137	277
Katete	51	64	115
Lundazi	161	117	278
All	352	318	670

5.4.2 Variable specifications in the outcome and selection equations

The dependent variable in our nutritional status model is stunting representing children who have low height-for-age z-score index, i.e. a z-score below -2. Stunting is preferred to the WHZ and WAZ indices because it represents the prevalence of long-term growth failure. The WHZ is a condition that usually reflects severely inadequate food intake and infection happening at present and, as such, it is recommended that WHZ should be regressed on flow and not stock variables (Christiaensen and Alderman, 2004). Weight-for-age on the other hand is a compound measure of height-for-age and weight-for-height which reflects body mass relative to age and thus making interpretation difficult (O'Donnell *et al.*, 2008).

Child characteristics

The explanatory variables relate to child, household, community and agricultural characteristics. Child level covariates include gender, age and whether or not the child had suffered from diarrhea in the past year. Some evidence from previous studies in Sub-Saharan Africa shows that boys are more likely to be stunted than girls (Ojiako *et al.*, 2009; Sanginga *et al.*, 1999: Svedberg 1990). However, some studies in Asia (e.g. Kumar *et al.*, 2006) show that girls are more stunted than boys; hence the impact of gender on stunting is indeterminate. Age of the child is an important determinant of the physiological characteristics which convert consumption into nutrition and nutrition into higher productivity and, therefore, higher earning potential (Sarmistha, 1999). Younger children are expected to have better nutritional status than the older children following commonly observed patterns in developing countries, explained by better child care and better feeding practices for younger children and exposure of older children to relatively harsh environment (Sanginga *et al.,* 1999). Illness of a child is hypothesised to negatively affect child nutrition. Diarrhea (proxy for illness) is expected to be inversely related to child nutritional status because it causes nutrients to flush through the intestinal tract too quickly to be absorbed (Apodaca, 2008). A repeatedly sick child may not consume adequate levels of food, which can result in growth retardation.

Household characteristics

Household characteristics include: age of the household head; gender of the household head; marital status of the household head; household size; education of the household head; highest grade attained by the most educated female of the household; number of household members above 65 years; number of household members below 15 years; number of adult females in the household (16-65 years old); household assets; cooperative membership (group membership); kinship and political connections. The gender of the household head is measured by a dummy variable equal to one for male headed households and zero for female headed households. Men are generally believed to be less involved than women in taking care of children and providing for their families' food needs (Onyango *et al.,* 1994). However, past studies have also shown that female headed households are usually poor relative to their male counterparts and therefore expenditure on child related nutrition is expected to be less than in male headed households. We therefore expect the sign on the gender of the household head to be either negative or positive. Similarly we expect the marital status of the household to have a positive effect on the nutritional status of children because children will have good care as both parents can take turns in looking after the child. Parental education is assumed to have a direct positive link to child nutrition through better child-care practices and resource allocation in the household. Education affects care giving practices through the ability to acquire skills and the ability to model behaviour (Chirwa and Ngalawa, 2008). In addition, to account for potential intra-household externalities from education, which are especially important in households at low education levels (Christiaensen and Alderman, 2004); we posit that the presence of educated female household members will have a positive effect on child nutritional status. It is assumed that household members who at least completed primary school are in a better position to comprehend and apply information related to children`s health.

Information gleaned from the literature shows that large family sizes impact negatively on nutritional status and household welfare in that the percentage of children under five, relative to total household size, reflects the burden of care in terms of nutrition finance, and parental time, and thus affects nutrition outcomes (Ajieroh, 2009). Household assets are often used as a proxy for household well-being or resources and some studies have shown that it is a positive determinant of child nutritional outcomes (Kabubo-Mariara *et al.,* 2008). Greater assets at household level allow people to spend more on important aspects of child nutrition such as health care, hygiene, food and clean water (Alderman *et al.,* 2005). We also expect the nutritional status to reduce with an increase in the number of household members below 15 years and above 65 (dependants) because with an increase in the number of dependants, we expect a greater burden on household resources for food consumption.

Group membership, kinship (number of relatives) and the number of relatives or friends in leadership positions (political connections) represent the household social networks. Previous studies have shown that cooperative group membership indicates the intensity of contacts with other farmers (Adegbola and Gardebroek, 2007), hence we expect farmers who are members of a group to have more information on improved maize varieties. Membership is therefore hypothesized to be positively associated with better child nutrition. Households with more relatives are more likely to have children who are better nourished as the household may have relatives they can rely on for critical support. However, an increase in the number of relatives may also come at the expense of income growth, which may negatively affect the nutritional status of children. Therefore the sign on kinship is indeterminate. Similarly, we expect households with political connections to have children who are well nourished as they can obtain support from their influential relatives/friends in times of problems.

Agricultural characteristics

To capture farm characteristics, we included adoption[23] of improved maize varieties, total land cultivated and distance to the nearest market. Adoption of improved maize varieties is expected to improve the nutritional status of children by promoting a link between food security and nutrition security (World Bank, 2008). Adoption of improved maize varieties leads to higher yields which in turn improves the food security status of farmers as well as increased income through sale of surplus food. The demand for productive agricultural land has been growing, partly due to the growing population in many developing countries. The more arable land under permanent crops or pastures, the more food there is and this in turn allows greater access to nutrition by increasing the availability of food (Apodaca, 2008). Distance to the nearest market reflects the transaction costs that the household incurs, such that the greater the distance, the higher the costs. We therefore expect distance to the nearest market to be negatively related with the nutritional status of the child.

Community characteristics

Sanitary conditions in the community are usually reflected in the percentage of households using toilets and the percentage of households who have access to safe drinking water from taps and deep, well-protected wells. Access to good toilet and safe drinking water facilities is expected to affect nutrition in a positive way as some studies have shown (Glewwe *et al.*, 2002; Christiaensen and Alderman, 2004; Chirwa and Ngalawa, 2008). Access to good sanitation may prevent the occurrence of infectious diseases such as diarrhea, dysentery and cholera which can adversely affect child nutrition. The distance to the health centre approximates the availability and costs of health services; therefore we expect the distance to the nearest health centre to be inversely related to the child nutritional status.

Factors that are hypothesised to affect adoption of improved maize varieties include household and social network characteristics mentioned above. For a detailed description of the hypothesized relationships between adoption and the variables used in the selection equation see Feder *et al.* (1985) and Kassie *et al.* (2013).

[23] An adopter in this study is defined as any farmer who planted or allocated land to at least one improved maize variety consistently for the past three years prior to the survey.

5.5 Socioeconomic characteristics of the sample households

Table 5.4 presents the characteristics of households in eastern Zambia. Considering all three districts, i.e. Chipata, Katete and Lundazi, on average 56% of the children were stunted, with Katete having slightly more with 57%. Table 5.4 further shows that about 23% were severely stunted, with Lundazi having the largest percentage of 26% of the severely stunted children. The average stunting rate (56%) for the three districts was higher than the average for the Eastern province of Zambia (50%) partly because we only considered three districts out of the 9 districts available in the province. Table 5.4 further shows that in our sample, about 53% of the children were girls with Lundazi having the highest number of almost 60%. The results also show that the average age of the children in the sample was 33 months and at least 60% of the children had diarrhea, the year preceding the survey. Lundazi had the highest number of children who had diarrhea with 73%, followed by Katete with 54% and this could be one of the reasons as to why these districts had relatively higher percentages of stunted children compared to Chipata district.

The average household size was 7.3 persons and across districts, it ranged from 8 persons in Lundazi to 6.6 persons in Katete with Chipata having 7.4 persons per household. At national level, the average household size in Zambia in 2010 was 5.2 persons (CSO, 2012), lower than the average in table 5.4. Inspection of table 5.4 reveals that most of the household heads completed primary school education with an average of 63%. To control for household resources, we included total household assets per capita. On average, the value of assets for the households was about ZMK1.23 million (US$237)[24], with Katete having the highest with ZMK1.34 million (US$258). Households in Chipata on the other hand had the lowest assets per capita with a total asset value of ZMK1.06 million (US$204). Most of the farmers belonged to a cooperative group with an average of about 92%, with Lundazi having the highest percentage of 96%.

[24] Exchange rate at the time of the survey: 1US$=ZMK5,197.

Table 5.4: Mean values of social economic characteristics of the sample households

District	Chipata	Katete	Lundazi	All
Child characteristics				
Normal stunting (> -2)	0.53	0.57	0.56	0.56
Moderate stunting (-3 to -2)	0.14	0.10	0.14	0.13
Severe stunting (< -3)	0.20	0.22	0.26	0.23
Child age (months)	31.98	33.38	33.98	33.11
Had diarrhea in the past one year (1= yes)	0.52	0.54	0.73	0.60
Gender (1= male)	0.49	0.56	0.42	0.47
Household Characteristics				
Gender of household head (1 = male)	0.68	0.70	0.71	0.69
Marital status (1= married)	0.85	0.87	0.92	0.89
Total household size (number)	7.38	6.56	7.99	7.31
Household completed primary school (1 = yes)	0.70	0.71	0.52	0.63
Asset per capita (000` ZMK)	1.06	1.34	1.30	1.23
Highest grade completed by most educated female (years)	6.68	6.30	7.47	6.94
Highest grade of most educated male (years)	7.55	6.83	8.66	7.67
Number of adult females in the household (16-65 years old) (number)	1.65	1.50	1.89	0.17
Number of household members above 65 years	0.21	0.14	0.22	0.20
Number of household members below 15 years	4	4	5	4
Kinship (Number of relatives)	4	4	3	4
Household has political connections (1 = yes)	0.66	0.60	0.62	0.63
Group membership (cooperative) (1 = yes)	0.91	0.83	0.96	0.92
Agricultural characteristics				
Total cultivated land (ha)	3.22	3.37	5.38	4.14
Adoption of improved maize varieties (1 = yes)	0.11	0.14	0.22	0.15
Distance to nearest market (minutes)	441	237	450	410
Community characteristics				
Distance to the nearest health center (minutes)	61.09	72.62	85.65	73.26
Access to toilets (sanitation) (1 = yes)	0.21	0.28	0.13	0.21
Access to safe water (1 = yes)	0.18	0.10	0.18	0.15

[a]ZMK = Zambian Kwacha.

As stated earlier, agriculture is a major source of livelihood and a key determinant of food security in rural areas. On average about 15% of the households adopted improved maize varieties, with Lundazi having the largest percentage of 22%. Household land ownership is an indicator of the household’s ability to withstand economic shocks and is also commonly used as a proxy for household income. Chipata had the lowest cultivated land (3.22 ha) while Lundazi had the highest with 5.38 ha. One of the reasons why Chipata had the lowest cultivated land is that among the three districts, Chipata is the most densely populated district and hence there is more pressure on the land. According to CSO (2012), Chipata district contributed about 27% to the population of the eastern province of Zambia, which was the largest amongst the three districts. Lundazi, on the other hand, is sparsely populated and therefore most farmers own relatively large pieces of land. However, owning large pieces of land may not necessarily translate into higher incomes as in the case of Lundazi, because it may also have to do with the quality and the capacity to work the land.

Table 5.4 also shows that on average, 28% of the households had access to toilet facilities in Katete and only 13% in Lundazi. Similarly, Chipata and Lundazi had the highest proportion of farm households who had access to drinking water with 18%. This is plausible because Chipata and Lundazi are relatively more urban than the Katete district.

The distribution of stunting by age and gender is presented in table 5.5. WHO (1995) recommends that at least two age disaggregation's be used, under 24 months and 24 months and over. The reason is that patterns of growth failure vary with age and the identification of determinants of malnutrition is facilitated. More girls (55%) in the 0-23 age category were stunted than boys (38%). Overall, the results show that the scourge of malnutrition affects older children (60%) more than younger ones (47%). This finding is consistent with other studies on the nutritional status of children in Africa (e.g. Ssewanyana, 2003; Kabubo-Mariara *et al.*, 2008).

Table 5.5: Child stunting by age and gender in Eastern Zambia

Age (months)	Male	Female	All
0-23	0.38	0.55	0.47
24-60	0.61	0.60	0.60

Table 5.6 shows the relationship between adoption of improved maize varieties and child stunting. Non-adopting households had more children who were stunted (57%) than those who adopted improved maize varieties (51%). This may imply that improved maize adoption has an effect on child stunting although we cannot make a causal inference at this stage.

Table 5.6: Child stunting by household adoption status and gender of child

Adoption status	Gender of child: Male	Female	All
Adopters	0.42	0.61	0.51
Non-adopters	0.58	0.56	0.57
All	0.55	0.56	0.56

5.5. Empirical Results

5.5.1 Determinants of child malnutrition

The estimated parameters for the endogenous switching probit (ESP) model, revealing the factors that affect child nutritional status, are presented in table 5.7. Estimates for the first stage regression for the determinants of improved maize adoption are presented in the appendix in table A5.1.

Child, household and community characteristics have differential impact among adopters and non-adopters (table 5.7). Among the child characteristics, only age (for non-adopters) and diarrhea (for adopters) are important determinants of long-term child malnutrition. Similar to the descriptive results above, the results in table 5.7 show that the probability of stunting increases with the age of the child among the non-adopters of improved maize varieties. As children grow older, weaning and less breast milk may make them more vulnerable to malnutrition (Kabubo-Mariara *et al.,* 2008). It may also suggest that as children grow older, less attention is given to them by their parents in terms of health care, the food they eat, and the nutritional value of the food. Similarly children who suffered from diarrhea the previous year before the survey were more stunted than those who did not and this is in line with our theoretical expectations. Food consumed by children suffering from diarrhea does not result in any meaningful nutrition for the child as nutrients flush through the intestinal tract too quickly to be absorbed.

In line with previous studies on child malnutrition (e.g. Kabubo-Mariara *et al.,* 2008) parental education reduced the probability of stunting by as much 75%. Similar to the results of Christiaensen and Alderman (2004), the presence of educated female adults in a household also had a significant correlation with the probability of stunting amongst children from adopting households. The probability of being stunted reduces by 16% with each additional year of schooling for the most educated female household member among adopters. This shows that educated females play an important role in sharing knowledge related to children`s health such as good child care practices and the ability to recognize illness. Presence of adult females in the household has a negative effect on the probability of stunting amongst non-adopters, implying that there is knowledge transfer related to child care from elderly to young mothers which in turn benefits the nutrition of the children.

Table 5.7: Determinants of child malnutrition in eastern Zambia

Variables	Adopters *(N = 106)*	Non-Adopters *(N = 564)*
	Coefficient	Coefficient
Age in months	0.01 (0.01)	0.01 (0.00)***
Gender of child	-0.65 (0.82)	-0.04 (0.13)
Child had diarrhea	0.87 (0.79)**	-0.12 (0.12)
Ln distance to health center	-0.18 (0.31)	0.07 (0.06)
Age of household head	0.00 (0.00)	0.00 (0.00)
Number of elderly (>65 years)	0.25 (1.25)	-0.16 (0.16)
Number of children (<15 years)	-0.14 (0.45	-0.05 (0.08)
Household completed primary school (1 = yes)	-0.75 (0.40)*	0.14 (0.13)
Gender of household head	-0.35 (0.38)	-0.07 (0.14)
Household size	0.04 (0.33)	0.08 (0.07)
Ln assets per capita	0.25 (0.35)	0.05 (0.06)
Highest grade completed by most educated female	-0.16 (0.10)*	-0.01 (0.02)
Number of adult females (16-65 years old)	0.44 (0.37)	-0.23 (0.10)**
Married	-1.47 (1.04)	0.42 (0.20)**
Group membership	-2.29 (1.06)**	-0.09 (0.20)
Kinship	0.05 (0.27)**	0.02 (0.01)*
Political connections	0.28 (0.72)	-0.02 (0.18)
Total land cultivated	0.03 (0.07)	-0.01 (0.02)
Ln distance to nearest village market	-0.20 (0.22)	0.02 (0.42)
Access to sanitation	0.99 (0.62)	-0.70 (0.15)***
Access to safe water	0.09 (0.43)	0.04 (0.11)
Chipata district dummy	-0.23 (0.61)	-0.06 (0.16)
Lundazi district dummy	-0.13 (0.76)	0.05 (0.18)
Constant	1.40 (10.77)	-1.03 (0.87)
Diagnostic tests		
Wald test	$\chi^2(26)$ =87.94; $p> \chi^2$ = 0.000	

*, **, and *** denotes significance level at 10%, 5% and 1% (Standard errors in parentheses).

Contrary to theoretical expectations, the results also show that marriage was not beneficial to the nutritional status of children among non-adopters. This may have to do with the age at which the mothers got married. Early marriages and young age of the mother have been linked with reduced nutritional outcomes for children (Raj *et al.*, 2010; Kabubo-Mariara *et al.*, 2008). This is so because young mothers may have low educational attainment, physically immature, socially and economically unstable (Bwalya *et al.,* 2015), all of which are associated with child malnutrition. Consistent with our theoretical expectations, household heads who were members of a cooperative were associated with better child nutrition. Similarly, the probability of stunting increased by between 2 and 5% among adopters and non-adopters, respectively, with kinship. This is so because the more relatives a household has, the more the pressure on household resources which may in turn result in poor nutrition especially among children.

Amongst the community variables, access to sanitation had a negative and significant effect on stunting among non-adopters. This can be partly attributed to the fact that with an improvement in sanitation, the elimination of parasites that cause infections such as diarrhea and dysentery is facilitated.

5.5.2 Impact of improved maize adoption on child malnutrition

The estimates for the average treatments effects (ATT), which show the impact of adoption on stunting after accounting for both observable and unobservable characteristics, are presented in table 5.8. Both adopters and non-adopters benefit from adoption. Specifically, the probability of stunting for children from adopting households would be 26% more had the households not adopted improved maize varieties. This is the average treatment effect on the treated (ATT) which is statistically significant at the 1% confidence level. Similarly, the probability of stunting for children from non-adopting households would be 33% less had the household adopted improved maize varieties, implying that non-adopting households would have realized lower rates of stunting from switching to improved maize varieties under the given conditions. This is the average treatment effect on the untreated (ATU) which is also statistically significant and implies that children from non-adopting households would be better off if their parents were to adopt improved maize varieties (as opposed to local varieties).

Table 5.8: Impact of improved maize varieties on child malnutrition (endogenous switching probit results)

Mean of outcome variable	Treatment effect	Average treatment effects (ATE)
Stunting	Farm households that adopted (ATT)	-0.26 (0.06)***
	Farm households that did not adopt (ATU)	-0.33 (0.02)***

*** denotes significance level at 1% (Standard errors in parentheses).

The results from the ESP model above may be sensitive to the exclusion restriction assumption; hence we also used the PSM approach to check the robustness of the estimated effects obtained from the ESP model. The same variables were used in the estimation of propensity scores as those reported in table A5.1. We followed Augurzky and Schmidt (2001) and Brookhart *et al.* (2006) in the implementation of propensity score estimation.

A visual inspection (figure 2) of the density distributions of the estimated propensity scores for the two groups indicates that the common support condition is satisfied: there was a substantial overlap in the distribution of the propensity scores of both adopter and non-adopter groups. The bottom half of the graph shows the distribution of propensity scores for the non-adopters and the upper half refers to the adopters.

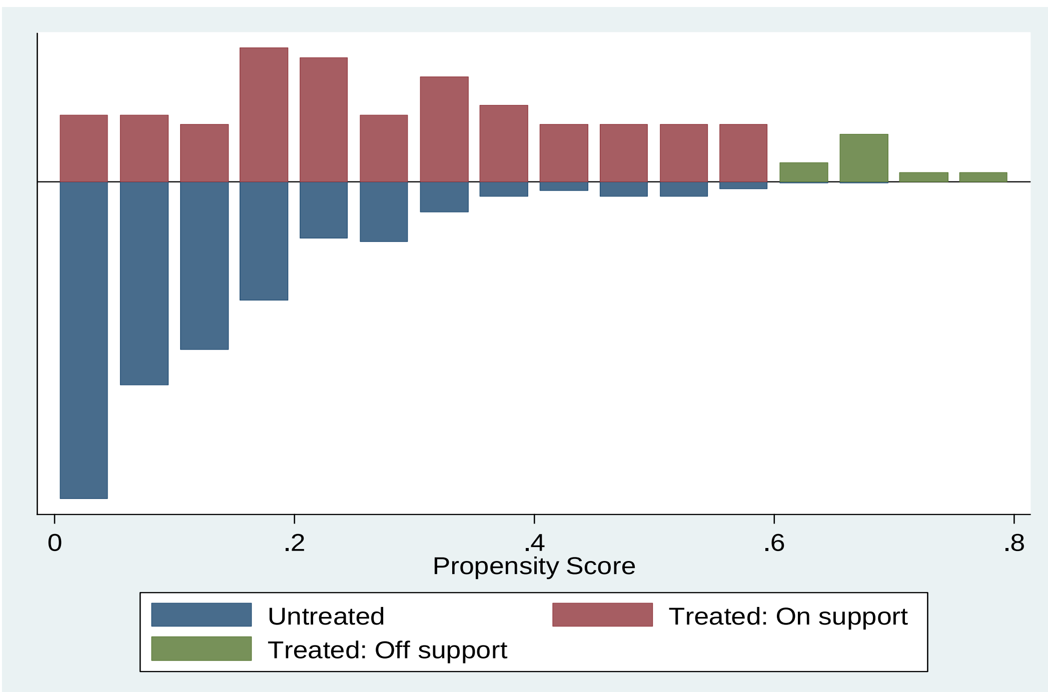

Figure 5.2: Propensity score distribution and common support for propensity score estimation.
Note**:** "Treated: on support" indicates the observations in the adoption group that have a suitable comparison. "Treated: off support" indicates the observations in the adoption group that do not have a suitable comparison.

Table 5.9 provides the ATT estimates from the PSM approach. The effect of improved maize varieties on stunting was estimated with the Nearest Neighbour (NNM) and the bias-adjusted NNM estimator developed by Abadie and Imbens (2011). Similar to the ESP results, adoption of improved maize varieties significantly reduces the probability of stunting. The causal effects from NNM approaches generally indicate that adoption of improved maize varieties exerts a negative and significant effect on stunting. Table 5.9 shows that on average, children from non-adopting households were relatively more stunted (62–63 %) than those from adopting households (51 %). Consistent with the ESP results reported in table 5.8, the PSM results suggest that adoption of improved maize varieties significantly reduces the probability of stunting in the range of 11–12%. Compared to the ESP results, the estimated effects from the PSM approach are relatively lower, probably because the latter does not take into account the selection on unobservables.

Table 5.9: Impact of Improved maize varieties on child malnutrition (matching results)

Matching Algorithm	Outcome variable	Means of outcome variables		ATT difference
		Adopters	Non Adopters	
Nearest Neighbor Matching	Stunting	0.51	0.63	-0.12 (0.07)*
Bias adjusted Nearest Neighbor Matching	Stunting	0.51	0.62	-0.11 (0.05)**

*, and ** denotes significance level at 10% and 5% (Standard errors in parentheses).

5.6. Conclusions and implications

This chapter analyses the factors that affect the nutritional status of under-five children as well as the impact of improved maize varieties on child stunting in Zambia using household survey data from a sample of 810 households in the eastern province of Zambia. Given the non-experimental nature of the data used in the analysis, a combination of parametric and non-parametric econometric methods was used to mitigate biases resulting from both observed and unobserved characteristics.

Empirical results show that child malnutrition is a function of the child’s age, gender of the household head, education of female household members, number of adult females in the household, and access to sanitation. The results are largely consistent with findings from other malnutrition studies (e.g. Christiaensen and Alderman, 2004; Kabubo-Mariara *et al.*, 2008).

Average treatment effects from both the ESP and PSM analysis show that adoption of improved maize varieties significantly reduced the prevalence of stunting. The ESP results show that farm households that adopted benefited more from adoption. The probability of stunting for children from adopting households was reduced by as much as 26%. The probability of stunting would have also reduced by about 33% for children from non-adopting households, if the households had adopted improved maize varieties, suggesting that non-adopting households would have realized lower rates of stunting from switching from growing local to improved maize varieties. Results from the matching estimates show that the probability of stunting also reduced among children from adopting households.

The results stress the key role of adoption of improved maize varieties in improving the income earning opportunities for rural households in order to fight the scourge of malnutrition. However, realizing the full benefits of improved technologies such as improved maize varieties in terms of improved income earning opportunities and food security will require increased investment and policy support aimed at enhancing technology adoption by farmers. Secondly, the significance of education in reducing child stunting suggests that the assimilation of nutritional messages may require more than basic education to be more effective. Promoting education among females is thus critical for nutrition-enhancing child care practices.

Appendix A5

Table A5.1: Probit estimates of determinants of adoption of improved maize varieties in Eastern Zambia

Variable	Coefficient
Age in months	0.01 (0.01)*
Gender of child	0.29 (0.14)**
Child had diarrhea	0.19 (0.15)
Ln distance to health center	-0.10 (0.07)
Age of household head	0.00 (0.00)
Number of elderly (>65 years)	-0.47 (0.17)**
Number of children (<15 years)	-0.23 (0.09)**
Household head Completed primary school (1 = yes)	-0.12 (0.16)
Gender of household head	-0.06 (0.16)
Household size	0.17 (0.07)**
Ln assets per capita	0.19 (0.06)***
Highest grade completed by most educated female adult	0.02 (0.02)
Number of adult females in the household (16-65 years old)	-0.14 (0.11)
Married	0.01 (0.50)
Group membership	0.02 (0.25)
Kinship	0.01 (0.01)
Political connections	0.37 (0.15)**
Total land cultivated	0.04 (0.02)**
Ln distance to nearest village market	0.02 (0.06)
Access to sanitation	-0.07 (0.20)
Access to safe water	-0.05 (0.15)
Chipata district dummy	-0.08 (0.22)
Lundazi district dummy	0.11 (0.20)
Access to NGO extension	0.13 (0.96)
Access to government extension	0.22 (0.14)
Distance to extension office	0.00 (0.00)**
Constant	-4.60 (0.00)***

*, **, and *** denotes significance level at 10%, 5% and 1% (Standard errors in parentheses).

CHAPTER 6

ADOPTION AND IMPACTS OF SUSTAINABLE AGRICULTURAL PRACTICES ON MAIZE YIELDS AND INCOMES: EVIDENCE FROM RURAL ZAMBIA[25]

Abstract

This chapter uses a multinomial endogenous treatment effects model and data from a sample of over 800 households and 3000 plots to assess the determinants and impacts of the adoption of sustainable agricultural practices (SAPs) on maize yields and household incomes in rural Zambia. Results show that adoption decisions are driven by household and plot level characteristics and that the adoption of a combination of SAPs raises both maize yields and incomes of smallholder farmers. Adoption of improved maize alone has greater impacts on maize yields, but given the high cost of inorganic fertilizer that limits the profitability of adoption of improved maize, greater household incomes are associated rather with a package involving SAPs such as maize-legume rotation and residue retention.

Key words: Maize yields; Incomes; Multinomial endogenous treatment effects; Sustainable agricultural practices; Zambia

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6.1 Introduction

Low soil fertility is one of the major constraints to agricultural productivity in Africa (Beedy *et al.,* 2010; Vanlauwe and Giller, 2006). Degraded and infertile soils resulting from continuous mono-cropping and insufficient recycling of organic matter coupled with rainfall variability and frequent dry spells have led to low crop yields in most of Africa (Ngwira *et al.*, 2012) and exacerbated poverty, food insecurity, and child malnutrition.

Sustainable agricultural practices (SAPs) offer a potential solution to some of these problems by improving soil fertility, sequestering carbon for climate change mitigation, and increasing crop yields and incomes. Broadly defined, SAPs may include crop rotation or intercropping with legumes, conservation tillage, residue retention, improved crop varieties, complementary use of organic fertilizers, and soil and stone bunds for soil and water conservation (Lee, 2005; Woodfine, 2009; Branca *et al.,* 2011). In this chapter we focus on three SAPs and combinations of them that relate to maize, a major crop in Zambia: maize-legume rotation, improved maize varieties, and residue retention. These three practices are the major practices included in Zambia’s conservation promotion policies (see section 6.2).

Maize-legume rotation has a number of benefits for both farmers and the environment, including soil improvement through nitrogen-fixation, reduction of disease, weed and insect populations, and increases in the soil-carbon content, which helps to mitigate the effects of climate change (Hutchinson *et al.,* 2007; Andersson *et al.,* 2014). Residue retention involves the accumulation of organic matter and, to a certain extent, minimum soil disturbance (conservation tillage) and offers additional benefits of improved soil fertility and crop yields. Moreover, it reduces soil and water losses, improves infiltration, reduces soil temperatures and, in time, improves soil fertility (CFU, 2007).

Although SAPs offer a number of benefits, there is limited empirical evidence on the determinants of their adoption and/or their impacts on smallholder welfare. A recent study by Arslan *et al.* (2013) on the adoption intensity of conservation agriculture (CA) in Zambia is the first attempt to comprehensively assess the factors that affect the intensity of adoption of SAPs. However, they only investigate the determinants and intensity of adoption (minimum tillage and crop rotation), and do not assess the effects on either crop yields or the welfare of the smallholder farmers. Similarly, Grabowski *et al.* (2014) assess only the determinants of the adoption of minimum tillage among cotton growing farmers in Zambia without looking at its impact on yields. Haggblade *et al.* (2010) give a good overview of the adoption and impact studies of CA in Zambia, where they show that CA has the potential of increasing yields and incomes for farmers. However, despite the potential complementarity of maize-legume rotation, residue retention, and improved maize, very few studies have simultaneously analysed the adoption and impacts of these three practices on smallholder farmer's welfare. Recent studies on adoption of SAPs use multivariate or seemingly unrelated multivariate probit regression models (Marenya and Barrett, 2007; Teklewold *et al.*, 2013a; Kassie *et al.*, 2013; Kamau *et al.*, 2014) to asses factors that affect adoption but do not analyse the impacts of (combinations of) these SAPs on crop yields and incomes of smallholder farmers. To our knowledge, the only studies that assess the impact of SAPs in Africa are by Teklewold *et al.* (2013b) and Kassie *et al.* (2014c) in Ethiopia and Malawi respectively. However, Ethiopia has different ecological conditions and agricultural policies (e.g. the seed sector is more liberalized in Zambia compared to Ethiopia) compared to Zambia, hence the impact of these SAPs may be different. We also include residue retention as one of the three SAPs as very little empirical evidence exists on the effects of residue retention (or a combination of residue retention with other SAPs) on crop yields and incomes. Neither Teklewold *et al.* (2013b) nor Kassie *et al.* (2014c) have analyzed the adoption and/or impacts of residue retention.

This chapter contributes to the emerging body of literature on SAPs by identifying the factors that affect the decisions to adopt individual practices of maize-legume rotation, residue retention, and improved maize as well as the combination of the three practices and their impact on smallholder farmers' welfare in Zambia. We model the adoption of these practices as a multinomial selection process where the expected benefits of SAPs induce the adoption decisions. We specifically use a multinomial endogenous treatment effects model (Deb and Trivedi, 2006b) to account for selection bias due to both observed and unobserved heterogeneity and to assess the differential impacts of the adoption of single as well as multiple SAPs. In assessing the adoption decisions, the multinomial endogenous treatment effects model allows the modelling of interdependency among the different SAPs. Compared with the computationally cumbersome multinomial endogenous switching regression model used by Teklewold *et al.* (2013b) and Kassie *et al.* (2014c), the multinomial endogenous treatment effects model is easier to implement and also allows the distribution of the endogenous treatment (adoption of SAPs) and outcomes (income and yield) to be specified using a latent factor structure, thereby allowing a distinction to be made between selection on unobservables and selection on observables (Deb and Trivedi, 2006b). In addition, the chapter uses comprehensive plot-level data combined with household level characteristics. The combination of plot and household level data allows us to build a panel which in turn helps to control for selection and endogeneity bias that may arise due to correlation of unobserved heterogeneity and observed explanatory variables.

The next section gives a background of SAPs in Zambia, while section 6.3 presents the data and description of variables. Section 6.4 describes the multinomial endogenous treatment effects model, followed by section 6.5 which presents the empirical results. The last section provides conclusions and implications.

6.2 Background of SAPs in Zambia

SAPs in Zambia have been promoted as a package under the practice known as Conservation Agriculture (CA), or Conservation Farming (CF) as well as through the promotion of improved crop varieties. CA in Zambia involves a package of several practices that includes land preparation in the dry season using minimum tillage systems, crop residue retention, seeding and input application in fixed planting stations, and crop rotations that include legumes (Haggblade and Tembo, 2003; CFU, 2007). The promotion of CA started in the 1990s as a result of ecological and economic challenges (Arslan *et al.*, 2013).

After Zambia's independence, agricultural production increased due, *inter alia*, to the expansion of the cultivated area, support for maize marketing, and extensive fertilizer and input subsidies (Baudron *et al.*, 2007). However, this encouraged continuous maize mono-cropping and a heavy application of inorganic fertilizers that resulted in soil degradation (Haggblade and Tembo, 2003; Andersson and D'Souza, 2013). These unsustainable agricultural practices coupled with the removal of maize subsidies and liberalization of maize marketing in 1991 led to a decline in maize productivity, increasing rural poverty and food insecurity (Baudron *et al.*, 2007; Andersson and D'Souza, 2013). It was in response to the above problems that the adoption of SAPs was encouraged in Zambia.

In Zambia, empirical evidence shows that CA is essential for smallholder agricultural production to be sustainable and to achieve broad based objectives of increasing crop yields, mitigating climate change and attaining food security (Arslan *et al.*, 2013; Umar *et al.*, 2011; Haggblade *et al.*, 2010). Adoption of improved crop varieties is the other SAP considered in this study (Lee, 2005). Improved maize varieties have been available in Zambia since the 1960s and were introduced to smallholder famers around the 1970s and to date about 60% of Zambian smallholders use improved maize seed (Kumar, 1994; Tembo and Sitko, 2013).

There are strong complementarities among the three practices (crop rotation, improved varieties and residue retention). Maize-legume crop rotation, which is one of the options for sustainable intensification, plays a vital role in fixing atmospheric nitrogen in the soil that is vital for increased maize production. The practice is also essential in controlling weeds, especially striga[26], which is notorious in fields were maize mono-cropping is the major practice. In the Southern province of Zambia, Thierfelder and Wall (2010) found that maize yields after growing sunhemp (a legume) were 74% higher than the yields in mono-cropped maize plots. The two practices are interrelated because the average yield per hectare is larger when both are adopted than when they are used in isolation. Similarly, the residues from both the production of legumes and improved maize improve soil fertility and moisture retention and increase soil organic matter once they are incorporated into the soil, which is beneficial for the production of both crops. Most African farmers face liquidity constraints (Marenya and Barrett, 2007), hence technologies such as maize-legume rotation can be used as a substitute for inorganic fertilizers (Kamau *et al.*, 2014) or complements, especially when it comes to producing hybrid maize.

SAPs should be able to meet the current and future societal needs for food and fibre and for ecosystem services and for healthy life by maximising the net benefit to society when all costs and benefits of the practices are considered (Tilman *et al.*, 2002). Therefore, sustainability is not only about ecology, but it also includes food security and economic aspects such as increased income and reduced poverty. With the growing population in Zambia, food production has to increase to meet the demand for food and one way to achieve this is the maintenance of high maize yields. Recent studies on adoption and impact of improved maize varieties in Zambia on smallholder farmers' well-being (e.g. Mason and Smale, 2013; Smale and Mason, 2014), show that improved maize varieties tend to increase crop yields, food security and household income. Moreover, the Zambia Agricultural Research Institute (ZARI) has released several improved maize varieties that are high yielding, early maturing, specifically adapted to each of the three agro-ecological zones of the country. For this reason, we consider improved maize varieties as being one of the sustainable agricultural practices.

[26] Striga, locally known as *kamfiti*, (witch weed in English) competes for soil nutrients with maize plants.

Additionally, as mentioned above, improved maize varieties (e.g. hybrids) require the use of complementary inorganic fertilizers, hence introducing improved varieties together with soil fertility enhancing practices such as residue retention and maize-legume rotation may reduce the need for fertilizer. Most recent studies (e.g. Vanlauwe *et al.*, 2014) recommend the use of supplementary fertilizers for SAPs to work properly. They explain that the use of fertilizer results in the production of more stover, which implies more organic matter in the soil.

In addition to the CA programme, a Fertilizer Support Programme (FSP) was reintroduced in Zambia in 2002 (MACO, 2008). The main objective of the FSP was to improve household and national food security, incomes, accessibility to agricultural inputs (seed and fertilizer) by smallholder farmers and building capacity of the private sector to participate in the supply of agricultural inputs. The FSP evolved into the current Farmer Inputs Support Programme (FISP) in 2008 with the view of enhancing diversification of the agricultural inputs (e.g. inclusion of legumes). Under this subsidy[27] programme, each beneficiary farmer receives 200 kg of fertilizer and 10 kg of hybrid maize seed. This programme has not led to heavy application of inorganic fertilizers and a return to maize mono-cropping. A recent study by Levine and Mason (2014) shows that FISP did not crowd out SAPs such as maize-legume rotation, although it had a small significant crowding out effect on minimum tillage, implying that farmers are still using these practices despite fertilizer subsidies.

6.3 Conceptual and econometric framework

6.3.1 Conceptual model

Agricultural technologies are usually introduced in packages that include several components. These components may complement each other, or may be adopted independently (Feder *et al.*, 1985). In most cases, farmers adopt a combination of technologies to deal with a whole range of agricultural production constraints including low crop productivity, droughts, weeds, pests, and diseases. The model developed by Feder (1982) presents one of the first attempts to deal with interrelations in the adoption of multiple agricultural technologies. In recent years, more studies have looked at the joint estimation of multiple agricultural technologies (e.g., Byerlee and De

[27] We don't conduct a detailed analysis of effects of subsidies on the beneficiaries in Zambia, but for details, see e.g., Mason and Smale (2013) and Smale *et al.* (2013).

Polanco, 1986; Dorfman, 1996; Marenya and Barrett, 2007). In this chapter, we utilise the random utility framework in modelling the adoption of the SAPs.

Here we focus on technology adoption as a choice over eight alternatives involving our three focus SAPs (crop rotation, improved varieties, and residue retention): (1) no adoption; (2) maize-legume rotation only; (3) improved maize varieties only; (4) residue retention only; (5) maize-legume rotation and improved maize; (6) maize-legume rotation and residue retention; (7) improved maize and residue retention; and (8) maize-legume rotation, improved maize, and residue retention. We presume that the farmer chooses the SAPs combination that maximizes utility subject to land availability, labour, input costs and other constraints. More formally, we assume that farmers aim to maximize their utility V_{ij} by comparing the utility provided by alternative varieties. A farmer *i* will therefore choose any practice *j*, over any alternative practice *k*, if $V_{ij} > V_{ik}$, $k \neq j$.

Farmers often self-select into the adopter/non-adopter categories and endogeneity problems may arise because unobservable factors may be correlated with the outcome variables (yields and total household income). For instance, farmers may decide to adopt a technology based on unobservable factors such as their innate managerial and technical abilities in understanding and using the technology (Abdulai and Huffman, 2014) and failure to account for this may overstate or understate the true impact of the SAPs.

To effectively assess the adoption and impact of SAPs in a joint framework, we adopt a multinomial[28] endogenous treatments effect model proposed by Deb and Trivedi (2006a, 2006b). The model accounts for both the interdependence of the adoption decisions and selection bias as a result of observed and unobserved characteristics. Adoption decisions are modelled in a mixed multinomial logit selection model in the first stage and in the second stage, OLS is used with selectivity correction to estimate the impacts of SAPs on maize yields and household income.

In addition, we exploit plot-level information to deal with the issue of farmers' unobservable characteristics that are likely to affect our results. In recent studies, plot level data have been used to construct a panel and to control for farm specific effects (e.g. Udry, 1996; Kassie *et al.*, 2008; Di Falco and Veronesi, 2013). Because of the complexity of including standard household fixed effects in a multinomial endogenous treatment effects model, we

[28]We use the multinomial as opposed to the multivariate framework because the former has an advantage of evaluating alternative combinations of practices as well as individual practices.

follow Mundlak (1978) to control for unobserved heterogeneity that may be correlated with observed explanatory variables. We include on the right-hand side of each equation the mean value of plot varying explanatory variables. The approach relies on the assumption that unobserved effects are linearly correlated with the means of the plot-varying explanatory variables.

6.3.2 Multinomial endogenous treatment effects model

The multinomial endogenous treatment effects model consists of two stages. In the first stage of the model, a farmer chooses one of the eight SAP bundles mentioned above. Following Deb and Trivedi (2006a, 2006b), let V_{ij}^* denote the indirect utility associated with the *j*th SAP bundle, $j = 0,1,2 \ldots J$ for household *i:*

$$V_{ij}^* = z_i'\alpha_j + \sum_{k=1}^{J} \delta_{jk} l_{ik} + n_{ij} \tag{1}$$

where z_i is a vector of household, social capital, trust and plot level covariates discussed in section 6.2; α_j is the vector of corresponding parameters to be estimated and; n_{ij} are the independently and identically distributed error terms; l_{ik} is the latent factor that incorporates the unobserved characteristics common to the household's adoption of SAPs and outcomes (maize yields and household income), such as the management and technical abilities of the farmers in understanding new technologies, and the transaction costs incurred as a result of poor access to input markets because of infrastructural constraints (Abdulai and Huffman, 2014). Following Deb and Trivedi (2006b), let *j* = 0 denote non-adopters and $V_{i0}^* = 0$. While V_{ij}^* is not observed, we observe the choice of SAP bundle in the form of a set of binary variables d_j and these are collected by a vector, $\mathrm{d}_i = (d_{i1},\ d_{i2},\ldots\ldots d_{iJ})$. Similarly, let $\mathrm{l}_i = (l_{i1}, l_{i2},\ldots.. l_{iJ})$. Then the probability of treatment can be written as:

$$\Pr(\mathrm{d}_i|z_i, \mathrm{l}_i) = g(z_i'\alpha_1 + \sum_{k=1}^{J} \delta_{1k} l_{ik} + z_i'\alpha_2 + \sum_{k=1}^{J} \delta_{2k} l_{ik} + \ldots + z_i'\alpha_J + \sum_{k=1}^{J} \delta_{Jk} l_{ik}) \tag{2}$$

where g is an appropriate multinomial probability distribution. Following Deb and Trivedi (2006b), we posit that g has a mixed multinomial logit (MMNL) structure defined as:

$$\Pr(\mathrm{d}_i|z_i, \mathrm{l}_i) = \frac{\exp(z_i'\alpha_j + \delta_j l_{ij})}{1 + \sum_{k=1}^{J} \exp(z_i'\alpha_k + \delta_k l_{ik})} \tag{3}$$

In the second stage, we assess the impact of adopting the SAP bundle on two outcome variables: the natural logarithm of maize yields and total household income per capita. The expected outcome equation is formulated as:

$$E(\mathrm{y}_i|d_i, \mathrm{x}_i, \mathrm{l}_i) = x_i'\beta + \sum_{j=1}^{J} \gamma_j d_{ij} + \sum_{j=1}^{J} \lambda_j l_{ij} \tag{4}$$

In this equation, y_i is the welfare outcome for a household i; x_i represent exogenous covariates with parameter vector β. Parameters γ_j denote the treatment effects relative to the non-adopters. Specifically, coefficients γ_j gauge the effects of SAPs on the welfare of farm households. If the decision to adopt SAPs is endogenous, assuming d_{ij} to be exogenous results in inconsistent estimates of γ_j. Since $E(\mathrm{y}_i|d_i, \mathrm{x}_i, \mathrm{l}_i)$ is a function of the latent factors l_{ij}, the outcome is affected by unobserved characteristics that also affect selection into treatment. When λ_j, the factor-loading parameter, is positive (negative), treatment and outcome are positively (negatively) correlated through unobserved characteristics; i.e., there is positive (negative) selection, with γ and λ the associated parameter vectors, respectively. Since the outcome variables are continuous, we assume that they follow a normal (Gaussian) distribution function. The resulting model was estimated using a Maximum Simulated Likelihood (MSL) approach[29].

Although in principle the parameters of the model are identified even if the regressors in the treatment equations are identical to those used in the outcome equation, Deb and Trivedi (2006a) recommend the use of exclusion restrictions or instruments for a more robust identification; i.e. including regressors in the treatment equations that do not enter the outcome equation. For the multinomial treatment effects model to be identified, it is not strictly necessary that the vector of covariates includes additional variables not included in the outcome equation because the parameters of the semi structural model can be identified through the nonlinear functional form of the selection model. Although getting a valid instrument is empirically challenging, we use source of SAPs information as the instrumental variable, which is a binary variable that takes on a value of one if information was obtained from a demonstration plot and

[29] The model was estimated using the Stata command *mtreatreg*, which is an extension of the *treatreg* Stata command to a multinomial approach by Deb (2009) and 500 simulation draws were used.

zero if no information on SAPs was obtained. Though in most cases the primary source of information is usually through government extension agents, demonstration plots are also important sources of information on improved agricultural technologies. Demonstration plots are likely to encourage the adoption of SAPs as farmers are able to see the benefits unlike just hearing about them. This variable is likely to be correlated with the adoption of SAPs but is unlikely to have any direct effect on maize yields or household incomes except through adoption. Adegbola and Gardebroek (2007) show that access to information on improved agricultural technologies is vital in the adoption decision making process, and information variables have been used as valid instrumental variables for technology adoption studies in Africa (Di Falco *et al.,* 2011; Di Falco and Veronesi, 2013). We establish the admissibility of the instrument by performing a simple falsification test: if a variable is a valid selection instrument, it will affect the decision of adopting SAPs, but will not affect the outcome variables among non-adopting farm households (Di Falco *et al.,* 2011; Di Falco and Veronesi, 2013). The results show that information on SAPs can be considered a valid instrument: it is statistically significant in most equations of the decision to adopt SAP *j* (table 1) but not of the yield and income equations (table 6.4A).

There is a potential simultaneity between adoption of improved maize varieties and inorganic fertilizers (Smale *et al.,* 1995). To control for this, we included a variable (fertilizer use), which is the average fertilizer application rate at the village level. This variable is expected to be exogenous to maize variety adoption decisions at plot level. The decision on the amount of fertilizer to apply to each plot is made at the household level. Therefore, aggregating fertilizer application rates at village level implies that the household has no influence on the amount of fertilizer applied and therefore is exogenous at plot and household level.

6.4 Data and description of variables

6.4.1 Sampling scheme

Our data come from a survey of 810 sample households and 3,750 maize plots conducted in January and February 2012 in the Eastern Province of Zambia. This was conducted by IITA and CIMMYT in collaboration with ZARI as part of a larger joint project entitled Sustainable Intensification of Maize-Legume Systems for the Eastern Province of Zambia (SIMLEZA). A survey questionnaire was prepared and administered by trained enumerators who collected data from households through personal interviews and observations. The survey was conducted in three districts (i.e., Chipata, Katete, and Lundazi), which were targeted as the major maize and legume growing areas. In the first stage, each district was stratified into agricultural blocks (8 in Chipata, 5 in Katete and 5 in Lundazi) as primary sampling units. In the second stage, 41 agricultural camps were randomly selected, with the number of camps allocated proportionately to the selected blocks, and the camps selected with the probability of selection proportional to size. Thus, 17 camps[30] were selected in Chipata, 9 in Katete and 15 in Lundazi. A total sample of 810 households was randomly selected from the three districts, with the number of households from each selected camp being proportional to the size of the camp.

Apart from household level data (e.g. age and education of the household head, size of the household), the survey also collected plot level data which includes the distance of the plot from the homestead, land tenure, size of the plot, depth of the soil, soil fertility, and slope of the plot. Data on crop yields, household income, and on the use of SAPs such as maize-legume rotation, residue retention and use of improved maize varieties were collected.

Total household income includes income from crops, livestock and livestock products, and off-farm income (e.g., salaries, remittances, farm labour wage income, pension income, and income from business). This provides a reliable indicator of economic well-being among smallholder farmers (Smale and Mason, 2014). Yield is defined as the total amount of maize harvested per hectare of land planted to maize in the growing season.

6.4.2 Description of variables and hypotheses

The factors that are likely to affect adoption and impact of SAPs include household and farm characteristics (Feder *et al.,* 1985) (age of the household head, education, household size, gender of household head, and farm size); social capital and trust (Isham, 2002; Narayan and Pritchett, 1999) (number of relatives in the village, membership of a farmers' associations, number of grain traders that farmers trust, confidence in extension agents, trust in government support in case of crop failure); number of contacts with extension agents; crop stresses (rainfall index, pests and drought problems); plot characteristics (land tenure, plot distance from homestead, soil fertility,

[30] A camp is a catchment area made up of 8 different zones consisting of villages and is headed by an agricultural camp officer. A block is made up of camps and is managed by an agricultural block officer.

slope and soil depth); and location characteristics (district dummies, distance to output market, and fertilizer markets).

Household characteristics

Feder *et al.* (1985) identify household size, age, education, and gender of the household head as important household characteristics that influence decisions on adoption of modern agricultural technologies. Adoption of SAPs may be affected by age because older farmers are expected to be more experienced with regards to production technologies and may have accumulated more physical and social capital (Kassie *et al.,* 2013). However, younger farmers may be more flexible in adopting innovations; hence the impact of age on technology adoption is indeterminate. Households with better education are expected to be more aware of the benefits of new technologies and more efficient in their farming practices (Pender and Gebremedhin, 2007). Similarly, size of the household is a factor that is often argued to be important in adoption decisions. Household size is usually used to proxy labour endowment (Pender and Gebremedhin, 2007), so that the larger the family, the more labour is available for agricultural production. Therefore the adoption of SAPs is expected to increase with both the level of education and size of the household. It is generally believed that women tend to adopt improved technologies at a lower rate than men (Doss and Morris, 2000) because they generally face constraints in terms of access to resources and time (Pender and Gebremedhin, 2007). We therefore hypothesise that female-headed households are less likely to adopt SAPs than their male counterparts.

The size of the farm and access to off-farm income are important measures of household wealth and can therefore influence the household decision making process. Farmers can allocate a larger area to improved varieties only if they have enough land; therefore those with more land have a comparative advantage to adopt SAPs. However, households with relatively more land may use less-intensive farming methods than those with less land (Kassie *et al.,* 2013). Hence the effect of farm size on the adoption of SAPs is indeterminate. Similarly, the effect of access to off-farm income on the adoption of SAPs could be positive or negative. Davis *et al.* (2009) review a number of papers on the impact of off-farm income on agriculture. They generally conclude that off-farm income has positive effects on agriculture. On the other hand, Mathenge *et al.* (2014b) found that off-farm income was inversely related to hybrid maize seed use in

Kenyan agricultural areas where farms were commercialising, intensification of maize production was relatively greater, and labour constraints were binding.

Social capital and trust

Previous studies have shown that social capital plays a vital role in the adoption of agricultural innovations (e.g. Isham, 2002; Narayan and Pritchett, 1999). Social networks enable farmers to overcome credit and resource constraints and are central in facilitating the exchange of information, especially where there is inadequate information and imperfect markets (Kassie *et al.*, 2013). The number of relatives in and outside the village on whom a household can rely for critical support (kinship) is an important factor in technology adoption. Households with more relatives are therefore more likely to adopt new technologies because they are able to experiment with technologies without excessive exposure to risk. However, Di Falco and Bulte (2011) mention that kinship sharing may come at the expense of income growth, which may reduce the likelihood of modern agricultural technologies being adopted. Therefore we do not have a clear prior expectation on the effect of kinship. Membership in an agricultural or farmers' association reflects the intensity of contacts with other farmers, enabling them to learn from one another about new technologies (Adegbola and Gardebroek, 2007). We therefore envisage that the adoption of SAPs will increase with group membership. The number of trusted traders that a farmer knows not only reflects the degree of market integration and incentive for sustainable intensification but also captures interlinked contracts that are common in the presence of imperfect markets. The coefficient on the number of trusted traders is expected to be positive since they play a vital role in spreading information about technologies, and offers market-outlet services to farmers (Teklewold *et al.*, 2013a).

Crop stresses

Most countries in sub-Saharan Africa are subject to environmental problems such as droughts, uneven distribution of rainfall and pests. SAPs are vital in reducing the risks associated with droughts because, among other things, they conserve moisture (residue retention) and reduce weeds, pests and diseases (crop rotation). Therefore we posit that occurrences of drought will positively affect adoption of SAPs. To measure the adequacy and distribution of rainfall, a rainfall index was constructed following Quisumbing (2003) based on questions such as whether rainfall came and stopped on time, whether there was enough rain at the beginning and during the growing season, and whether it rained at harvest time. Responses to each of the questions (yes or no) were coded as favourable or unfavourable rainfall outcomes and averaged over the number of questions asked, so that the best outcome would be equal to one and the worst to zero. We expect the coefficient on the rainfall index to be positive. Since high rainfall may encourage weed growth (Kassie *et al.*, 2010), crop rotation, which reduces weeds, is especially expected to be positively associated with high levels of rainfall.

In the recent past, warmer weather has led to an increase in the number of pests and diseases and SAPs such as maize-legume rotation provide an alternative that can be used to maintain crop productivity (Delgado *et al.*, 2011). Kassie *et al.* (2013) explain that farmers tend to adopt practices that involve smaller cash outlays and low-risk technologies such as crop rotation in the presence of pests and diseases. However, SAPs such as residue retention have also been associated with an increase in diseases such as maize root rot (Govaerts *et al.*, 2007). We therefore hypothesise that pests will be positively associated with crop rotation and negatively related to residue retention and improved maize seeds.

Location characteristics

The distance to input and output markets reflects the transaction costs associated with buying inputs and taking produce to the market. Apart from affecting the access to the market, these distances can also affect the availability of new technologies, information and credit institutions (Kassie *et al.*, 2013). We therefore expect the relationship between the distance to the market and adoption of SAPs to be negative.

Access to extension services

Agricultural extension is proxied by the number of contacts farmers have with public and private extension agents and their confidence in their skills. The frequency of contacts is expected to have a positive effect on the adoption of SAPs based on previous studies on technology adoption (e.g. Adegbola and Gardebroek, 2007), reflecting exposure to information on SAPs. However, extension agents are involved in a lot of activities that include delivering inputs and administering credit, hence farmers may question their skills (Teklewold *et al.*, 2013a). Therefore, we hypothesise that confidence in the skills of extension agents (yes or no responses to the question whether farmers trusted the skills extension agents working in their area) will be positively associated with adoption.

Plot characteristics

Finally, plot level characteristics are significant determinants of adoption (e.g. Pender and Gebremedhin, 2007; Kassie *et al.*, 2008; Teklewold *et al.*, 2013a). The distance from the homestead is expected to reduce the likelihood of adoption for reasons explained above. In addition, plots that are further away may receive less attention and monitoring (Teklewold *et al.*, 2013a), making them more susceptible to pests and theft. Households that own land are expected to adopt modern agricultural technologies more easily as they do not run the risk of ending land rental. Other plot characteristics that are expected to influence adoption include farmers perception of the fertility of the plot (ranked as good, medium and poor), the slope of the plot (ranked as gentle, medium and steep) and soil depth (ranked as deep, medium and shallow). Poor soil fertility is expected to be positively associated with fertility enhancing practices such as maize-legume rotation and residue retention; the propensity to adopt SAPs such as improved maize is expected to be greater on plots with fertile soils, because most improved maize varieties require the application of expensive inorganic fertilizers which most rural farmers cannot afford (not all rural farmers have access to subsidies).

Plots with steep slopes are susceptible to wind and water erosion, so soil conservation practices such as residue retention, together with crop rotation are important in improving the structural stability and preventing run-off of soil nutrients (Anderson, 2009). We expect the coefficient on steep and moderate slopes to be positively associated with residue retention and crop rotation, but negative with improved maize seed. The depth of the soil gives an indication of the volume which can be utilised by the plant and which is conducive to moisture retention. This implies that the deeper the soil the better, hence we expect that deep and medium soils will increase the likelihood of SAPs being adopted.

The decision to adopt improved maize varieties is usually made jointly with the use of inorganic fertilizers (Kumar, 1994; Smale *et al.,* 1995). Some studies in the region have also shown the importance of fertilizer in raising agricultural yields especially of maize (e.g. Duflo *et al.,* 2008). On the other hand, maize-legume rotation and residue retention are essential in enhancing soil fertility and maybe used as substitutes for inorganic fertilizers. We therefore expect the relationship to be positive with improved maize seed and negative with maize-legume rotation and residue retention.

6.5 Results and discussion

6.5.1 Descriptive statistics

Summary statistics of the explanatory variables that are hypothesised to influence adoption are presented in tables A6.1 and A6.2 in the appendix. Table A6.1 presents the descriptive statistics for the variables used in the analysis disaggregated by district. Maize-legume rotation (11%) and residue retention (13%) were the most popular SAPs among adopters, for individual components, and 51% in combination. Maize is usually rotated with legumes such as groundnuts, common beans, cowpeas, and soybeans. Maize-legume rotation was the most common practice implemented in Chipata (13%) compared with 8% for Katete and 10% for Lundazi. The three SAPs were adopted simultaneously on about 13% of the 3,750 plots, whereas about 4% did not adopt any SAP. Lundazi district had the highest percentage of farmers (14%) who simultaneously adopted the three SAPs. About 64% of plots received improved maize varieties regardless of the adoption of other SAPs. However, farmers use improved maize alone on only 1% of total plots.

Considering the relationship between fertilizer and the other SAPs, the descriptive statistics show that adopters of maize-legume rotation and residue retention applied less fertilizer than non-adopters (see table A6.3 in the appendix). As expected, adopters of improved maize seeds applied more fertilizer than non-adopters, and when combined with (especially) legume rotation, the additional fertiliser use is reduced as the rotation substitutes for fertiliser.

The descriptive statistics also show that the welfare measures of interest in this chapter (maize yields and household income) are generally higher for Lundazi district (table A6.1) and for multiple SAPs as compared with the individual SAPs (table A6.2). The results also show that household income is highly correlated with the adoption of improved maize only and the combination of improved maize and residue retention.

6.5.2 Determinants of adoption

Table 6.1 presents parameter estimates of the mixed multinomial logit model which is equivalent to the first stage of our multinomial endogenous treatment effects model. The base category is non-adoption against which results are compared. The model fits the data very well with the Wald test, $\chi2= 86.37$; $p> \chi^2= 0.000$ implying that the null hypothesis that all the regression coefficients are jointly equal to zero is rejected.

The results show that adoption of most packages increases with household size. As expected, education is significantly and positively associated with most of the SAPs. Education plays an important role in technology adoption in that it enables households to interpret new information and understand the importance as well as benefits of adopting modern agricultural technologies. Our results suggest that female-headed households are less likely to adopt most of the SAP packages. This is consistent with the findings of some previous studies (e.g. Doss and Morris, 2000). This may reflect the fact that women have less access to resources, such as land, education and information on improved agricultural technologies (Doss and Morris, 2000)

Land is also important in technology adoption decisions, especially land-enhancing technologies such as SAPs. We find that households that have larger pieces of land are more likely to adopt SAPs than those with less land. Similarly, households who have rented pieces of land (land tenure) are less likely to adopt the SAP packages than those who have their own land. This result is consistent with a number of studies on technology adoption in Africa that have shown that land ownership has a significant effect on adoption decisions (e.g. Kassie *et al.,* 2013; Teklewold *et al.,* 2013a).

The results also show that access to off-farm income reduces the likelihood of adoption of certain SAP packages. This is consistent with Pender and Gebremedhin (2007) and Mathenge *et al.* (2014b) who found a similar result. The relationship between off-farm income and technology adoption can be negative because off-farm activities divert time and effort away from agricultural activities, reducing investments in technologies and the availability of labour.

Farm households that have less trust in government support are more likely to adopt crop and risk diversifying practices believing that government support may not satisfy households' food diversity needs (Kassie *et al.,* 2013). This is evidenced by the negative relationship between the government support variable and adoption of the all the SAPs (except residue retention). Consistent with earlier work on technology adoption (e.g. Adegbola and Gardebroek, 2007), contact with government extension agents has a positive and significant effect on the decision to adopt the package that includes the combination of all the SAPS, but not for all other combinations.

As expected, problems with pests are mainly associated with residue retention, maize–legume rotation and residue retention and the combination of all three SAPs. Research has shown that insect-pests may be sheltered in undisturbed soils and crop residues on the soil surface thereby being carried over from one season to another (Jat *et al.*, 2013). Furthermore, Jat *et al.*(2013) explain that during the initial adoption of SAPs such as conservation agriculture, higher incidences of insect-pests are possible when parasites or predators that would eliminate the pests are insufficient.

The results in table 6.1 further show that occurrence of droughts is positively related to the adoption of maize-legume rotation only and in combination with residue retention and improved maize. This is consistent with the findings of a recent study in Zambia (Arslan *et al.*, 2013) showing that SAPs such as CA are essential in mitigating risks from climate change. Crop rotation enables farmers to grow crops that can be harvested at different times and that may require different weather or environmental conditions. Residue retention on the other hand is vital in improving the soil and retaining moisture especially in drought prone areas. The result therefore suggests that farmers are adopting these practices to reduce the effects of droughts.

Distance to fertilizer and output markets influence the adoption of improved maize seed and combination of improved maize seeds and residue retention. This reflects the transaction costs of purchasing inputs so that the further away a farmer is from the market, the higher the transactions costs and consequently the lower the likelihood that they would adopt SAPs.

Table 6.1: Mixed multinomial logit model estimates of adoption of SAPs in eastern Zambia (baseline category is non-adoption of SAPs)

Variable	Residue retention	Maize-legume rotation	Maize-legume rotation and residue retention	Improved maize	Improved maize and residue retention	Improved maize and maize-legume rotation	Residue retention, maize-legume rotation and improved maize
Age of the household head	-0.01 (0.01)	0.00 (0.01)	0.01 (0.01)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.01 (0.01)*
Education of household head	0.06 (0.03)*	0.08 (0.03)**	0.13 (0.03)***	0.06 (0.07)	0.13 (0.04)	0.11 (0.05)**	0.20 (0.03)***
Total household size	0.04 (0.04)	0.13 (0.04)***	0.10 (0.03)***	-0.21 (0.09)**	0.10 (0.04)**	0.16 (0.05)***	0.13 (0.04)***
Gender of household head	-0.74 (0.24)***	-0.63 (0.24)**	-0.80 (0.22)***	-0.13 (0.49)	-1.34 (0.27)***	-0.06 (0.39)	-0.95 (0.24)***
Total owned land in ha (cultivated)	0.11 (0.04)**	0.07 (0.04)	0.15 (0.04)***	0.21 (0.06)***	0.14 (0.04)***	0.06 (0.06)	0.18 (0.04)***
Access to off-farm income	-0.41 (0.22)*	-0.33 (0.23)	-0.53 (0.20)**	0.72 (0.49)	-0.32 (0.25)	0.43 (0.36)	-0.40 (0.22)*
Kinship	0.01 (0.02)	0.00 (0.02)	0.00 (0.02)	0.00 (0.04)	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)
Group membership	0.09 (0.4)	-0.51 (0.39)	-0.36 (0.36)	-0.08 (0.75)	0.21 (0.50)	0.71 (0.85)	0.89 (0.45)**
Trust in government support	-0.32 (0.29)	-0.67 (0.29)**	-0.73 (0.27)**	-0.91 (0.48)*	-0.75 (0.32)**	-1.20 (0.38)***	-0.75 (0.29)**
Number of traders	-0.03 (0.03)	-0.03 (0.03)	0.00 (0.02)	0.02 (0.04)	0.02 (0.03)	-0.06 (0.05)	0.00 (0.03)
Confidence in skills of extension staff	-0.06 (0.3)	-0.53 (0.3)*	-0.22 (0.28)	-0.14 (0.65)	-0.07 (0.34)	0.41 (0.50)	-0.16 (0.30)
Contacts with government extension agent	0.00 (0.01)	-0.03 (0.01)	0.01 (0.01)	0.02 (0.02)	0.01 (0.01)	-0.03 (0.02)	0.02 (0.01)**
Contacts with government extension agent	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	-0.02 (0.02)	0.01 (0.01)	0.01 (0.01)	0.00 (0.01)
Rainfall index	-0.04 (0.22)	0.32 (0.23)	-0.11 (0.20)	-0.21 (0.44)	-0.10 (0.26)	0.44 (0.37)	-0.35 (0.22)
Pests are a problem	-0.69 (0.29)**	-0.34 (0.29)	-0.80 (0.26)***	-0.61 (0.55)	-0.18 (0.33)	-0.35 (0.44)	-0.66 (0.29)**
Droughts are problem	1.02 (0.51)	1.28 (0.51)**	0.95 (0.49)*	0.06 (1.17)	1.39 (0.55)**	0.13 (0.80)	0.99 (0.52)*
Ln distance to fertilizer markets	0.03 (0.09)	-0.11 (0.09)	-0.08 (0.08)	-0.23 (0.14)*	-0.05 (0.10)	-0.12 (0.12)	-0.11 (0.09)
Ln distance to output market	-0.18 (0.11)	0.01 (0.11)	-0.08 (0.10)	0.15 (0.20)	-0.35 (0.12)***	-0.19 (0.15)	-0.13 (0.11)
Katete	0.72 (0.37)**	0.12 (0.38)	0.63 (0.35)	0.14 (0.91)	0.96 (0.42)**	-1.18 (0.84)	0.47 (0.37)
Lundazi	-0.98 (0.26)	-1.38 (0.26)***	-1.97 (0.23)***	0.16 (0.51)	-0.38 (0.30)	-0.79 (0.37)**	-1.69 (0.26)***
Mundlak fixed effects							
Mean plot distance	0.10 (0.10)	-0.04 (0.10)	0.01 (0.09)*	-0.11 (0.20)	0.08 (0.12)	-0.27 (0.16)	0.00 (0.10)
Mean land tenure	-1.21 (0.46)**	-0.42 (0.49)	-0.79 (0.44)	-1.09 (0.74)	-1.42 (0.49)**	-1.44 (0.58)**	-1.03 (0.47)**
Mean good fertility	0.29 (0.30)	0.57 (0.30)*	0.54 (0.27)**	0.62 (0.56)	0.38 (0.35)	1.01 (0.49)**	0.55 (0.31)*
Mean medium fertility	0.21 (0.28)	0.08 (0.29)	0.84 (0.26)***	-0.39 (0.63)	0.30 (0.34)	0.37 (0.49)	0.82 (0.3)**
Mean gentle slope	-0.49 (0.54)	-0.13 (0.55)	-0.74 (0.49)	0.57 (1.03)	-0.57 (0.61)	-0.36 (0.9)	-0.97 (0.53)*
Mean medium slope	-0.34 (0.55)	-0.31 (0.56)	-0.77 (0.50)	-0.27 (1.09)	-0.62 (0.63)	-0.13 (0.91)	-0.97 (0.55)
Mean deep soil	0.25 (0.37)	0.27 (0.38)	0.16 (0.34)	0.06 (0.72)	0.74 (0.45)	1.97 (0.78)**	0.52 (0.38)
Mean medium deep soil	0.48 (0.36)	0.29 (0.37)	0.60 (0.32)*	-0.69 (0.73)	0.65 (0.44)	1.58 (0.78)**	0.61 (0.37)
Fertilizer use	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)	0.00 (0.0 0)
Instrumental variable							
Had information on SAPs	0.49 (0.22)**	0.80 (0.23)***	0.88 (0.20)***	-0.11 (0.47)	0.34 (0.26)	0.43 (0.34)	0.61 (0.23)**
Constant	3.21 (1.06)***	2.04 (1.07)*	4.01 (0.97)***	0.44 (1.98)	2.26 (1.23)*	-1.85 (1.78)	0.92 (1.10)
Wald test	χ^2= 86.37;	$p > \chi^2$= 0.000					

Notes: Sample size is 3750 plots and 810 households and 500 simulation draws were used. *, **, and *** denotes significance level at 10%, 5% and 1% (Robust standard errors in parentheses). Fixed effects at plot level are included.

Considering the plot characteristics, good soil fertility increases the adoption of the combination of maize-legume rotation and residue retention, improved maize and maize-legume rotation and a package of all the SAPs compared with those plots with poor soil fertility. However, this result should be interpreted with caution because good soil fertility may be endogenous to crop rotation and residue retention since these practices lead to an improvement in soil fertility. Without any information on plot history, causal inferences based on this result may be misleading. The likelihood of adoption of a package consisting of all the practices is lower on plots with gentle slopes compared with plot with steep plots. However, the likelihood of adoption of a package of improved maize and maize-legume rotation or residue retention and maize-legume rotation is greater on plots with deep and medium deep soils.

6.5.3 Average treatment effects of SAPs

Table 6.2 presents the estimates of the impact of SAPs on maize yields and household incomes[31]. For comparison, the outcome variables are estimated under the assumptions of exogenous and endogenous adoption decision of SAPs.

With the assumption of exogenous adoption of SAPs, the results show that, on average, adopters had higher yields than non-adopters and the results are positive and statistically significant for most of the packages. The results for income per capita are similar to those for the maize yields. Making causal inferences based on the assumption of exogenous SAPs may be misleading as it ignores the effect of unobserved confounders. The difference in welfare outcomes could be caused by unobservable characteristics of the farm households, such as their management abilities. We address this issue by estimating a multinomial endogenous treatment effects model.

The average adoption effects after controlling for unobserved heterogeneity show a somewhat different picture (table 6.2). Generally, SAPs adopted in combination had a strong and positive impact on maize yields and household income compared to those adopted in isolation, except for the adoption of improved maize which out yielded the more comprehensive package consisting of improved maize, residue retention, and maize legume-rotation. In addition, most of the factor loadings (λ) show evidence of negative selection bias suggesting that unobserved factors that increase the likelihood of adopting SAPs are

[31] The results for the two normal regressions (second stage) are presented in table A6.5 in the appendix. The results for the mixed multinomial treatment effects regressions are not presented to conserve space, but are available upon request.

associated with lower levels of welfare than those expected under random assignment to the SAPs adoption status. Positive selection bias is also evident in the income equation suggesting that unobserved variables increasing the likelihood of adopting residue retention are associated with higher levels of income.

The results show that, on average, the adoption of improved maize varieties significantly increases maize yields by about 90% and this is consistent with other studies on adoption and impacts of improved maize varieties (e.g. Mason and Smale, 2013). Considering the adoption of a combination of maize-legume rotation and residue retention and the package consisting of improved maize and residue retention, the average gain from adoption is about 67% and 57% increase in maize yields for adopters compared with that of non-adopters. The impacts of these packages are less than that of the adoption of improved maize only probably because some farmers may have accessed fertilizers through the government subsidy programme, which may have led to the increased yields[32]. This is consistent with the descriptive statistics showing that more inorganic fertilizers were applied to improved maize than other packages. Results further show that the implementation of a more comprehensive package consisting of all the three SAPs results in the yield effect of 80% (table 2). Consistent with Arslan *et al.* (2015), we find no significant effect of maize-legume rotation on maize yields when implemented in isolation. Compared with the results under the exogeneity assumption, the estimates with the unobservable characteristics controlled for are generally higher, suggesting that failure to account for endogeneity would understate the true impact of adoption.

For income per capita, results show that on average adopters of a combination of SAPs had between 43% and 75% more income than non-adopters, with the package of improved maize and residue retention having the greatest income effect. Maize-legume rotation has a positive and significant effect (69%) on income when combined with improved maize. Interestingly, we find that the impacts of SAPs on income when all three SAPs are adopted as a package were lower than the returns from SAPs packages involving improved maize and maize-legume rotation or improved maize and residue retention. Contrary to the results found by Teklewold *et al.* (2013b), this suggests that adopting a more comprehensive SAPs package may not necessarily result in higher income than a package consisting of two SAPs. Similar findings are reported by Di Falco and Veronesi (2013) who show that

[32] Second stage estimates show that inorganic fertilizers had a positive and significant impact on maize yields.

implementing climate change adaptation strategies that are more comprehensive does not always translate into higher net revenues when compared with less comprehensive strategies.

Table 6.2: Multinomial endogenous treatment effects model estimates of SAPs impacts on maize yields and household income

Assumption	Package	Ln maize yield per ha	Ln household income per capita
Exogenous	Residue retention	26% (0.14)*	25% (0.18)
	Maize-legume rotation	36% (14)**	48% (0.18)**
	Improved maize	38% (0.13)***	26% (0.16)
	Maize-legume rotation and residue retention	58% (0.27)**	50% (0.34)
	Improved maize and residue retention	46% (0.16)***	50% (0.2)**
	Improved maize and maize-legume rotation	17% (0.22)	46% (0.27)*
	Residue retention, maize-legume rotation and improved maize	58% (0.14)***	62% (0.18)***
Endogenous	Residue retention	43% (0.17)**	-12% (0.22)
	Maize-legume rotation	-6% (0.18)	29% (0.27)
	Improved maize	90% (0.15)***	54% (0.19)**
	Maize-legume rotation and residue retention	67% (0.29)***	39% (0.35)
	Improved maize and residue retention	57% (0.20)***	75% (0.24)***
	Improved maize and maize-legume rotation	33% (0.23)	69% (0.31)**
	Residue retention, maize-legume rotation and improved maize	80% (0.17)***	43% (0.24)*
	Selection terms (λ)		
	Residue retention	-0.19 (0.11)*	0.43 (0.15)**
	Maize-legume rotation	0.51 (0.12)***	0.22 (0.24)
	Improved maize	-0.64 (0.1)***	-0.37 (0.13)**
	Maize-legume rotation and residue retention	-0.10 (0.10)	0.12 (0.10)
	Improved maize and residue retention	-0.11(0.13)	-0.29 (0.14)**
	Improved maize and maize-legume rotation	-0.18 (0.09)*	-0.23 (0.16)
	Residue retention, maize-legume rotation and improved maize	-0.25 (0.12)*	0.24 (0.18)

Notes: The baseline is farm households that did not adopt any SAP. Sample size is 3750 plots and 810 households and 500 simulation draws were used. *, **, and *** denotes significance level at 10%, 5% and 1% (Standard errors in parentheses). Fixed effects at plot level are included.

6.6 Conclusions and implications

6.6.1 Conclusions

In many developing countries, smallholder farmers face multiple constraints such as low soil fertility that lead to low yields and farm incomes. Previous studies have shown that adoption of SAPs can play an important role in alleviating some of these problems. However, in most studies, much attention has been given to the understanding of the determinants of adoption of multiple SAPs without analysing their effect on the welfare of farmers. This chapter contributes to the empirical literature in this area by examining the determinants and impacts of the adoption of three interdependent SAPs (crop rotation, improved varieties, and residue retention) and their combinations on maize yields and household incomes in rural Zambia using a multinomial endogenous treatment effects model and farm household survey data collected from a sample of over 800 households.

As in most adoption studies, we find that the decision to adopt is a function of household and plot level characteristics. Specifically, the education of the household head, household size, farm size, and the occurrence of droughts increase the likelihood of farm households adopting SAPs. On the other hand, the propensity to adopt reduced with gender of the household head, access to off-farm income, and distance to input and output markets. The finding of a highly significant and positive association between adoption of SAPs and the occurrence of droughts suggests that farmers may be using SAPs to mitigate the risks of rainfall variability and climate change.

On the impact of adoption of SAPs on welfare outcomes, the results show that sample selection bias results if the welfare equations are estimated without considering the adoption decision. The impact results also show that SAPs adopted in combination or as a package are more effective than those adopted in isolation. The adoption of the package that includes improved maize only and the bundle consisting of improved maize and residue retention resulted in the highest yield and income effects, respectively. Similarly, adoption of a comprehensive package of all the SAPs provides the second highest increase in yield. Although improved maize seed results in the highest benefits in farmers welfare, adoption of improved maize also entails the use of inorganic fertilizers which maybe expensive for most small scale farmers. The results of this chapter show that other relatively inexpensive soil enhancing practices, such as the combination of residue retention with crop rotation and a combination of these SAPs with improved maize can equally increase maize yields and incomes.

6.6.2 Policy implications

The impact estimates highlight that a more comprehensive package would not always result in greater benefits than less comprehensive packages. Consistent with the knowledge-intensive nature of most of the SAPs, the results suggest that improvement in education should be one of the strategies to improve adoption of SAPs. Moreover, removal of barriers to information would greatly help in encouraging adoption. It is also important for the actors involved in the design, promotion and dissemination of SAPs to find a suitable mix of these practices that will ensure an increase in maize productivity and incomes, while at the same time addressing issues related to inorganic fertilizer application, rainfall variability, droughts and climate change in Zambia.

In the wake of the ever increasing costs of external inputs such as inorganic fertilizers, there is need for policy makers and researchers to look for cheaper alternatives of increasing yields and incomes for small scale farmers. Adoption of improved maize varieties in combination with practices such as maize-legume rotation and residue retention can boost yields and farm incomes and should be promoted especially among resource poor farmers who cannot afford inorganic fertilizers.

Appendix A6

Table A6.1: Descriptive statistics by district

	Chipata	Katete	Lundazi	All
Variables	Mean	Mean	Mean	Mean
Dependent variables				
Household income per capita (ZMK million)[a]	1.26 (1.86)	1.51 (1.87)	3.62 (1.28)	2.21 (2.09)
Maize yields (Kg/ha)	2275 (2946)	2583 (2024)	3182 (5817)	2686 (4162)
SAPs j				
No adoption of SAPs	0.03 (0.17)	0.02 (0.12)	0.07 (0.25)	0.04 (0.20)
Residue retention only	0.12 (0.32)	0.14 (0.34)	0.13 (0.34)	0.13 (0.33)
Maize-legume rotation only	0.13 (0.33)	0.08 (0.27)	0.10 (0.30)	0.11 (0.31)
Improved maize only	0.01 (0.07)	0.00 (0.05)	0.02 (0.14)	0.01 (0.10)
Maize-legume rotation and residue retention	0.54 (0.49)	0.59 (0.49)	0.42 (0.49)	0.51 (0.50)
Improved maize and residue retention	0.03 (0.18)	0.05 (0.21)	0.08 (0.28)	0.05 (0.23)
Maize-legume rotation and improved maize	0.02 (0.13)	0.00 (0.05)	0.03 (0.17)	0.02 (0.14)
Residue retention, maize-legume rotation and improved maize	0.12 (0.33)	0.12 (0.33)	0.14 (0.35)	0.13 (0.34)
Household characteristics				
Age of household head (Years)	42.66 (14.43)	43.87 (12.69)	43.26 (13.95)	43.16 (13.88)
Education of household head (Years)	5.71 (3.62)	5.69 (3.50)	7.45 (3.12)	6.36 (3.51)
Household size (Number)	6.94 (3.17)	6.83 (3.17)	7.77 (3.30)	7.23 (3.25)
Gender of household head (1=Male)	0.64 (0.48)	0.66 (0.47)	0.69 (0.46)	0.66 (0.47)
Total cultivated land (ha)	3.26 (3.17)	3.61 (2.99)	5.26 (4.49)	4.09 (3.80)
Access to off-farm income (1=Yes)	0.63 (0.48)	0.59 (0.49)	0.62 (0.49)	0.62 (0.49)
Had information on SAPs	0. 58 (0.49)	0.65 (0.48)	0.59 (0.49)	0.60 (0.49)
Social capital and trust				
Kinship (number)	4.54 (9.38)	4.02 (4.26)	4.00 (6.18)	4.22 (7.32)
Group membership (1=Yes)	0.88 (0.32)	0.86 (0.35)	0.97 (0.16)	0.91 (0.28)
Trust in government support (1=Yes)	0.82 (0.39)	0.81 (0.39)	0.75 (0.43)	0.79 (0.41)
Number of trusted traders (Number)	1.97 (5.02)	1.07 (2.60)	1.44 (3.92)	1.57 (4.18)
Extension services				
Confidence in extension agents (1=Yes)	0.81 (0.39)	0.72 (0.45)	0.80 (0.40)	0.79 (0.41)
Contact with government extension agents (number)	8.71 (16.80)	16.24 (33.89)	12.98 (19.32)	12.01 (22.77)
Pests are a problem (1=Yes)	0.14 (0.35)	0.11 (0.31)	0.11 (0.31)	0.12 (0.33)
Droughts are a problem (1=Yes)	0.12 (0.33)	0.11 (0.32)	0.04 (0.20)	0.09 (0.29)
Rainfall index (1=Good)	0.72 (0.45)	0.58 (0.49)	0.70 (0.46)	0.68 (0.47)
Location characteristics				
Distance to output market (Minutes)	442.14 (546.42)	268.93 (148.53)	542.59 (1070.66)	441.43(753.37)
Distance to seed market (Minutes)	411.06 (576.44)	206.94 (138.47)	405.52 (894.57)	363.47(668)
Distance to fertilizer market (Minutes)	396.55 (519.97)	221.23 (138.36)	549.62 (1107.64)	415.19(768.33)
Plot Characteristics				
Plot distance	19.62 (23.73)	37.03 (40.62)	15.04 (26.24)	21.77 (30.29)
Tenure (1= Owns land)	0.92 (0.28)	0.95 (0.21)	0.91 (0.29)	0.92 (0.27)
Good soil fertility (1=Yes)	0.36 (0.48)	0.28 (0.45)	0.40 (0.49)	0.36 (0.48)
Medium soil fertility (1=Yes)	0.42 (0.49)	0.44 (0.50)	0.47 (0.50)	0.44 (0.50)

Table A6.1. (continued)

	Chipata	Katete	Lundazi	All
Variables	Mean	Mean	Mean	Mean
Poor soil fertility (1=Yes)	0.22 (0.41)	0.27 (0.45)	0.13 (0.34)	0.20 (0.40)
Gentle slope (1=Yes)	0.51 (0.50)	0.44 (0.50)	0.61 (0.49)	0.53 (0.50)
Medium slope (1=Yes)	0.46 (0.50)	0.51 (0.50)	0.34 (0.47)	0.43 (0.49)
Steep slope (1=Yes)	0.02 (0.15)	0.04 (0.20)	0.05 (0.22)	0.04 (0.19)
deep soil (1=Yes)	0.40 (0.49)	0.35 (0.48)	0.29 (0.45)	0.35 (0.48)
Medium soil depth (1=Yes)	0.51 (0.50)	0.57 (0.50)	0.61 (0.49)	0.56 (0.50)
Shallow soils (1=Yes)	0.08 (0.28)	0.07 (0.26)	0.09 (0.29)	0.09 (0.28)
Fertilizer use (kg/ha)	121.11 (88.80)	119.97 (108.15)	184.22 (480.24)	144.72 (306.35)
Number of observations	1510	847	1393	3750

Notes: The sample size refers to the total number of plots. The final total sample includes 810 farm households and 3750 plots. The reference for soil fertility, slope, and soil depth is poor soil fertility, steep slope, and shallow soils. Standard deviations in parentheses.

[a] The exchange rate at the time of the survey was US$1= ZMK5197.

Table A6.2: Descriptive statistics by adoption of SAPs

Variable	Non-adoption of SAPs	Residue retention	Maize-legume rotation	Maize-legume rotation and residue rotation	Improved maize varieties	Improved maize and residue retention	Improved maize and maize-legume rotation	Improved maize , Maize-legume rotation and residue retention
	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
Dependent variables								
Household Income per capita (ZMK million)	1.72 (2.62)	1.91 (7.51)	1.55 (2.96)	1.90 (6.20)	3.50 (4.13)	4.40 (18.72)	3.89 (9.07)	3.32 (11.39)
Maize yields (kg/ha)	2236 (2511)	2178 (2180)	2560 (3611)	2734 (4679)	3014 (2307)	2611 (2401)	2972 (3173)	3015 (4604)
Household characteristics								
Age of household head (Years)	42.67 (15.19)	41.25 (13.32)	43.07 (14.43)	43.55 (14.10)	41.54 (12.29)	41.98 (12.40)	42.40 (12.04)	44.52 (13.45)
Education of household head (Years)	5.71 (3.21)	5.86 (3.43)	5.79 (3.40)	6.36 (3.57)	6.79 (3.47)	6.86 (3.42)	7.14 (2.85)	7.20 (3.43)
Household size (Number)	6.54 (2.44)	6.71 (2.93)	7.30 (3.16)	7.25 (3.31)	5.77 (2.62)	7.36 (2.87)	8.15 (3.94)	7.81 (3.50)
Gender of household head (1= Male)	0.76 (0.43)	0.65 (0.48)	0.66 (0.48)	0.66 (0.47)	0.74 (0.44)	0.54 (0.50)	0.76 (0.43)	0.68 (0.47)
Total cultivated land (ha)	3.28(2.71)	3.75 (3.24)	3.52 (3.46)	4.12 (3.82)	4.94 (5.50)	4.35 (4.00)	3.88 (3.52)	4.91 (4.45)
Access to off-farm income (1= Yes)	0.69 (0.47)	0.61 (0.49)	0.62 (0.49)	0.61 (0.49)	0.79 (0.41)	0.62 (0.49)	0.76 (0.43)	0.62 (0.49)
Had information on SAPs	0.42 (0.50)	0.56 (0.50)	0.59 (0.49)	0.64 (0.48)	0.41 (0.50)	0.55 (0.50)	0.53 (0.50)	0.61 (0.49)
Social capital and trust								
Kinship (Number)	3.97 (6.46)	4.62 (7.71)	4.07 (6.82)	4.09 (6.70)	3.74 (5.52)	4.17 (4.65)	4.47 (6.60)	4.19 (8.63)
Group membership (1= Yes)	0.92 (0.27)	0.91 (0.28)	0.88 (0.33)	0.90 (0.30)	0.90 (0.31)	0.95 (0.23)	0.97 (0.17)	0.97 (0.17)
Trust in government support (1= Yes)	0.86 (0.35)	0.84 (0.37)	0.78 (0.42)	0.79 (0.40)	0.72 (0.46)	0.76 (0.43)	0.67 (0.47)	0.77 (0.42)
Number of trusted traders (Number)	1.47 (2.96)	1.33 (2.38)	1.32 (3.54)	1.64 (4.87)	2.15 (3.70)	2.16 (4.72)	1.39 (2.81)	1.59 (3.44)
Confidence in extension agents (1= Yes)	0.86 (0.35)	0.82 (0.39)	0.76 (0.43)	0.77 (0.42)	0.90 (0.31)	0.82 (0.38)	0.89 (0.32)	0.80 (0.40)
Extension services								
Contact with government extension agents (Number)	7.80 (11.15)	10.21 (16.85)	9.17 (19.52)	12.50 (23.09)	5.95 (10.22)	15.08 (28.95)	15.94 (36.10)	14.86 (26.62)
Contact with NGO extension agents (Number)	3.46 (9.69)	3.50 (8.71)	2.48 (6.67)	5.25 (13.17)	4.05 (9.44)	4.08 (8.41)	2.90 (4.79)	7.23 (21.40)
Crop Stresses								
Rainfall index (1= Good)	0.69 (0.46)	0.68 (0.47)	0.74 (0.44)	0.67 (0.47)	0.64 (0.49)	0.70 (0.46)	0.79 (0.41)	0.65 (0.48)
Pests are a problem (1= Yes)	0.22 (0.41)	0.11 (0.31)	0.15 (0.36)	0.10 (0.30)	0.18 (0.39)	0.16 (0.37)	0.17 (0.38)	0.11 (0.32)
Droughts are a problem (1= Yes)	0.03 (0.18)	0.10 (0.29)	0.12 (0.33)	0.09 (0.29)	0.03 (0.16)	0.09 (0.29)	0.04 (0.20)	0.09 (0.28)

Table A6.2. (continued)

Variable	Non-adoption of SAPs	Residue retention	Maize-legume rotation	Maize-legume rotation and residue rotation	Improved maize varieties	Improved maize and residue retention	Improved maize and maize-legume rotation	Improved maize , Maize-legume rotation and residue retention
	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
Location characteristics								
Distance to output market (Minutes)	923.03 (1370.93)	491.53 (887.01)	537.46 (899.08)	388.24 (600.99)	742.41 (1163.82)	359.68 (757.15)	415.26 (603.80)	389.87 (674.21)
Distance to seed market (Minutes)	836.84 (1394.49)	419.47 (804.79)	437.43 (867.55)	304.14 (425.43)	743.08 (1356.39)	408.70 (938.53)	298.40 (614.48)	296.01 (467.75)
Distance to fertilizer market (Minutes)	947.02 (1432.16)	466.38 (877.30)	463.16 (875.04)	364.23 (617.44)	850.51 (1470.44)	374.09 (817.03)	327.90 (395.84)	361.81 (687.32)
Plot distance (Minutes)	22.77 (34.97)	26.40 (37.56)	20.87 (36.99)	21.54 (27.47)	16.74 (29.95)	22.96 (26.06)	15.31 (19.02)	19.82 (29.12)
Tenure (1= Owns land)	0.95 (0.38)	0.90 (3.65)	0.94 (0.59)	0.93 (2.96)	0.90 (0.70)	0.85 (0.55)	0.83 (0.74)	0.91 (4.54)
Good soil fertility (1= Yes)	0.36 (0.48)	0.37 (0.48)	0.41 (0.49)	0.33 (0.47)	0.49 (0.51)	0.42 (0.50)	0.46 (0.50	0.35 (0.48)
Medium soil fertility (1= Yes)	0.42(0.49)	0.39 (0.49)	0.34 (0.48)	0.48 (0.50)	0.23 (0.43)	0.39 (0.49)	0.36 (0.48)	0.47 (0.50)
Poor soil fertility (1= Yes)	0.22 (0.40)	0.23 (0.43)	0.24 (0.43)	0.18 (0.39)	0.28 (0.46)	0.19 (0.39)	0.18 (0.39)	0.23 (0.38)
Gentle slope (1= Yes)	0.61 (0.49)	0.54 (0.50)	0.54 (0.50)	0.52 (0.50)	0.67 (0.48)	0.56 (0.50)	0.56 (0.50)	0.53 (0.50)
Medium slope (1= Yes)	0.37 (0.49)	0.44 (0.50)	0.42 (0.49)	0.44 (0.50)	0.31 (0.47)	0.39 (0.49)	0.42 (0.50)	0.41 (0.49)
Steep slope (1= Yes)	0.01 (0.11)	0.03 (0.16)	0.03 (0.18)	0.04 (0.20)	0.03 (0.16)	0.04 (0.20)	0.03 (0.17)	0.06 (0.23)
deep soil (1= Yes)	0.50 (0.50)	0.56 (0.50)	0.49 (0.50)	0.59 (0.49)	0.38 (0.49)	0.50 (0.50)	0.49 (0.50)	0.56 (0.50)
Medium soil depth (1= Yes)	0.40 (0.49)	0.36 (0.48)	0.41 (0.49)	0.31 (0.46)	0.51 (0.51)	0.43 (0.50)	0.49 (0.50)	0.35 (0.48)
Shallow soils (1= Yes)	0.09 (0.29)	0.06 (0.23)	0.10 (0.30)	0.09 (0.29)	0.10 (0.31)	0.08 (0.27)	0.03 (0.17)	0.09 (0.29)
Fertilizer use (kg/ha)	133.81 (90.05)	118.79 (88.02)	121.11 (119.17)	144.98 (371.04)	182.64 (123.25)	182.64 (123.25)	139.92 (109.91)	176.25 (373.33)
Number of observations	153	470	411	1906	39	206	72	493

Notes: The sample size refers to the total number of plots. The final total sample includes 810 farm households, and 3750 plots. The reference for soil fertility, slope and soil depth is poor soil fertility, steep slope and shallow soils. Standard deviation in parentheses.

Table A6.3: Fertilizer application by SAPs

Package	Total fertilizer applied (Kg/ha) Mean	Mean
	Non-adopters	Adopters
Residue retention	148.64	117.00
Maize-legume rotation	147.73	119.96
Maize-legume rotation and residue retention	145.15	144.28
Improved maize	143.93	219.54
Improved maize and residue retention	142.18	188.88
Improved maize and maize-legume rotation	144.40	150.44
Improved maize , maize-legume rotation and residue retention	140.35	173.84

Table A6.4: Parameter estimates: Test on validity of selection instruments

Variables	Ln Maize yields/ha	Ln Household per capita income
Education of household head	0.26 (0.07)***	0.17 (0.08)**
Total household size	0.00 (0.09)	-0.21 (0.08)**
Gender of household head	-0.93 (0.39)***	-0.86 (0.56)
Total owned land in ha (cultivated)	-0.14 (0.04)***	0.10 (0.09)
Access to off-farm income	0.31 (0.46)	0.12 (0.57)
Kinship	0.00 (0.02)	-0.03(0.02)
Group membership	-0.26 (0.58)	0.40 (0.63)
Rely on government support	0.15 (0.6)	2.50 (1.02)**
Number of trusted traders	0.05 (0.05)	0.20 (0.08)**
Confidence in skills of extension staff	-0.96 (0.54)*	-1.12 (0.58)*
Contacts with NGOs extension agent	-0.01 (0.01)	-0.02 (0.01)*
Contacts with government extension agent	0.01 (0.03)	0.06 (0.02)**
Rainfall index	1.34 (0.43)	1.39 (0.55)**
Insects are a problem	-0.20 (0.4)	-2.01(0.53)***
Droughts are problem	0.17 (0.51)	-0.60 (0.44)
Ln Distance to the fertilizer markets	-0.20 (0.11)*	-0.34 (0.21)
Ln Distance to the output market	0.22 (0.13)	0.49 (0.23)**
Katete district	1.06 (0.67)	0.94 (0.60)
Lundazi district	-0.05 (0.32)	-0.13 (0.45)
Mean ln plot distance	-0.36 (0.24)	-0.38 (0.20)*
Mean tenure	1.39 (0.71)*	0.56 (0.74)
Mean good fertility	0.78 (0.53)	1.17 (0.53)
Mean medium fertility	-0.82 (0.65)	0.15 (0.64)
Mean gentle slope	1.15 (1.06)	0.90 (1.22)
Mean medium slope	1.77(1.17)	1.40 (1.32)
Mean deep soil	0.03 (0.55)	0.38 (0.64)
Mean medium deep soil	-0.26 (0.43)	-0.36 (0.6)
Fertilizers rate	0.00 (0.00)	0.00 (0.00)
Had information on SAPs	0.61 (0.41)	-0.34 (0.40)
Constant	4.19 (1.45)**	8.98 (1.62)***
Number of observations	153	153

Notes: *, **, and *** denotes significance level at 10%, 5% and 1% (Standard errors in parentheses). Fixed effects at plot level are included.

Table A6.5: Second stage estimates for maize yields and household income

Variables	Ln Maize yields/ha	Ln Household income per capita
Age of the household head	-0.01 (0.00)**	-0.01 (0.00)***
Education of household head	0.00 (0.01)	0.03 (0.01)***
Total household size	0.01(0.01)	-0.08 (0.01)***
Gender of household head	0.04 (0.06)	0.36 (0.07)***
Total owned land in ha (cultivated)	-0.02 (0.01)**	0.16 (0.01)***
Access to off-farm income	0.32 (0.05)***	1.04 (0.07)***
Kinship	-0.01(0.00)*	0.01 (0.00)*
Group membership	0.41 (0.09)***	0.44 (0.12)***
Rely on government support	-0.10 (0.06)	-0.17 (0.08)***
Number of trusted traders	0.03 (0.01)***	0.05 (0.01)***
Confidence in skills of extension staff	-0.24 (0.07)***	-0.25 (0.08)***
Contacts with NGO government extension agent	-0.01 (0.00)***	0.00 (0.00)
Contacts with government extension agents	0.01 (0.00)***	0.01 (0.00)***
Rainfall index	0.16 (0.06)**	0.31 (0.07)
Insects are a problem	-0.08 (0.08)	-0.39 (0.10)***
Droughts are problem	0.07(0.09)	0.07 (0.11)
Ln distance to the fertilizer market	-0.03 (0.02)	-0.09 (0.03)***
Ln distance to the output market	0.12 (0.03)***	0.15 (0.03)***
Katete district	0.36 (0.07)***	0.42 (0.09)***
Lundazi district	0.35 (0.07)***	0.48 (0.08)***
Ln plot distance	-0.11 (0.02)***	-0.08 (0.03)**
Mean land tenure	-0.20 (0.10)***	-0.51 (0.12)***
Mean good fertility	0.35 (0.08)***	0.25 (0.1)**
Mean medium fertility	0.11 (0.08)	0.24 (0.10)**
Mean gentle slope	0.34 (0.13)**	0.07 (0.17)
Mean medium slope	0.53 (0.13)***	0.28 (0.17)
Mean deep soil	-0.40 (0.10)***	-0.12 (0.13)
Mean medium deep soil	-0.50 (0.10)***	-0.30 (0.12)**
Fertilizer use	0.00 (0.00)***	0.00 (0.00)***

Notes: *, **, and *** denotes significance level at 10%, 5% and 1% (Standard errors in parentheses). Fixed effects at plot level are included.

CHAPTER 7

SYNTHESIS

7.1 Introduction

Agriculture in sub-Saharan Africa is the main source of income, food security and employment for a majority of people, especially the poor, and thus directly supports human development (UNDP, 2012). However with the increasing population, producing more food in the coming decades, while at the same time combating poverty and hunger, is a major challenge facing African agriculture (Garrity et al., 2010). Not only should agricultural productivity increase, but this also has to be done in a sustainable fashion in order to give rise to meaningful development. Productivity gains can be obtained by technological change as embodied in improved or modern crop varieties and sustainable agriculture practices. Technological change in agriculture can contribute to poverty reduction directly through increased production for home consumption, higher gross revenues from sales and lower production costs; and indirectly through the effects which adoption can have on the price of food for consumers, employment and wage effects in agriculture for both poor and non-poor farmers (de Janvry and Sadoulet, 2002). This thesis contributes to the understanding of how adoption of improved agricultural technologies (i.e. improved maize and SAPs) affects smallholder farmers' household welfare.

This thesis generally contributes to the vast literature on agricultural technology adoption by providing innovative ways of estimating impacts attributable to improved maize adoption and SAPs as well as useful policy insights that can contribute to the promotion of these technologies. In chapter 3, we show that improved maize adoption is important in increasing income and reducing poverty. In Chapter 4, we use subjective and objective measures of food security to show that improved maize adoption is important in increasing household food security. In chapter 5 we test the agriculture—nutrition nexus by examining the role of improved maize in reducing child malnutrition. In chapter 6, we assess the effect of adopting SAPs (including maize) either as a single technology or as a package, in which we find that adopting a package of technologies resulted in higher income. The synthesis of these four core chapters is summarized in section 7.2. In the remainder of this chapter I will discuss the main findings of the thesis and provide policy implications and avenues for future research in the subsequent sections.

7.2 Summary of the main results

In most adoption and impact studies, agricultural technologies are often modelled separately using single equation models. In in this thesis, we depart from this standard approach and model adoption of improved maize varieties and SAPs and their associated impacts on several welfare indicators using simultaneous and multinomial equation models. Using these approaches, we examine the determinants and impact of improved maize varieties and SAPs on the welfare of smallholder farmers in the Eastern province of Zambia. The results on the determinants of adoption from the four core chapters (chapters 3-6) were pretty much standard, consistent with many adoption studies (e.g. Ali and Abdulai, 2010; Zellera *et al.*, 1999; Marenya and Barrett, 2007). Regarding the impact of improved maize and SAPs on the smallholder farmer's welfare, several welfare indicators were used including, maize yields, household income, food security, and poverty and child malnutrition. Consistent with the impact pathway in figure 1.2, adoption of improved maize varieties and SAPs increased maize yields (chapter 6), household income (chapters 3 and 6), food security (chapter 4) and child malnutrition (chapter 5).

Specifically, it was mentioned in chapter 1 that poverty, food insecurity and child malnutrition are among the major problems facing most rural smallholder farmers in Zambia. In chapters 3, 4, 5 and 6, we ask the question of whether adoption of improved maize and SAPs has an effect on maize yields, poverty, household food security and child malnutrition status of the farm households. The results of this thesis show that adopters of improved maize and SAPs realized higher yields that non-adopters. The increase in maize yields resulted in an increase in crop income which is a major contributor to household income for most rural households. The results in chapter 3 evidently show that the adoption of improved maize varieties increased crop income, household income and reduced the probability of being poor. Consistent with figure 1.2, the increased yields and income among improved maize adopting households clearly had beneficial effects on household food security. It suffices to mention that in measuring food security, both objective and subjective measures of food security were used. This was so, because although there is widespread agreement that measuring food security is important, the crucial question of how to do so remains contentious and unclear (Upton *et al.*, 2015). On one hand some researchers advocate for the use of objective measures such as per capita income, off-farm income, per capita food expenditure and the amount of calories consumed by the households (e.g. Babatunde and Qaim, 2010; D'Souza and Jolliffe, 2013). On the other hand subjective measures of food security are also becoming important because unlike objective measures, they are able to capture psychological dimensions of food insecurity (Headey and Ecker, 2013). One intriguing finding though was that outcomes based on objective food security measures were higher than the subjective measures and this could be attributed to the fact that the food expenditure measure maybe prone to either under or overestimation. It is also possible that the households deliberately reported their food security status to be low, expecting support from the organization conducting the interviews. This is the moral hazard risk mentioned by Pinstrup-Andersen, (2009). This thesis also made a methodological contribution to the literature on the impacts of agricultural innovations (see chapter 4). Specifically, one of the problems encountered in impact evaluation is misspecification of the adoption and outcome equations. We accounted for this by using doubly robust impact evaluation method that guards against the misspecification of both equations. Taken together, the results of Chapters 3 and 4 are in line with the emerging body of literature on agricultural technologies and objective and subjective measures of food security (e.g. Mathenge *et al.*, 2014a, and Becerril and Abdulai, 2010; Headey, 2013a; Kassie *et al.,* 2014a; Shiferaw *et al.,* 2013). The results in these chapters not only show that improved maize is an important crop in reducing poverty and food insecurity, but also underscores the importance of modelling the impacts in simultaneous equation framework. More importantly though, we also learned that adoption would have equally benefited non-adopters, had they decide to adopt improved maize varieties. This finding represents an addition on most of the previous impact studies on maize.

In chapter 1, it was also mentioned that poverty and food insecurity are among the most important underlying causes of child malnutrition. The results from chapters 3 and 4 reveal that adoption of improved maize can directly reduce poverty and household food insecurity through an increase in the household income and more consumption arising from improved yields. But can the same be said on the effects on child malnutrition? Chapter 5 extends the results of chapters 3 and 4 by examining the determinants of child nutritional status and the impact of improved maize on child malnutrition. As figure 1.2 shows, reduced poverty and food insecurity is associated with reduced child malnutrition levels. Increase in household income may also help households to spend more on nutritious food which can be vital for children's growth. Elsewhere, most nutrition studies did not find a link between agriculture and child nutrition (Masset *et al.,* 2011). Masset *et al.* (2011) attributes this partly to the faulty designs and methodology used in previous studies. The results in this thesis on the determinants of child nutrition were largely consistent with other studies in Africa (e.g. Christiaensen and Alderman, 2004; Kabubo-Mariara *et al.,* 2008; Zeng *et al.,* 2014). Similar to the results in chapter 3, the factors hypothesized to affect nutrition had a differential effect on child malnutrition depending on whether the child came from an improved maize adopting or non-adopting household. Another interesting finding was that adoption of improved maize varieties significantly reduced the prevalence of stunting. This implies that improved maize not only improves welfare and food security of farm households (as shown in chapters 3 and 4), but also reduces child malnutrition. This is an important finding because, first; the results are not only consistent with those in chapters 3 and 4, but also established a causal link between improved maize adoption and child nutrition which has been problematic. Second, the under-five child nutritional status is increasingly becoming an important key performance indicator in measuring the impact of many development projects (e.g. poverty (Setboonsarng, 2005), and food security (FAO, 2013)), hence demonstrating that the adoption of improved maize varieties reduces child malnutrition, is an important finding.

In chapters 3 to 5, emphasis was placed on establishing whether adopting improved maize alone had an effect on selected household welfare indicators. In most cases, farmers adopt a combination of technologies to deal with a whole range of agricultural production constraints including low crop productivity, droughts, weeds, pests and diseases (see chapter 6). In chapter 6, we build on the previous chapters and combine improved maize with two other SAPs with the idea of examining whether SAPs adopted in combination (package) leads to higher benefits (e.g. yields and income) than those adopted in isolation. As figure 1.2 depicts, adoption of SAPs increased both yields and income. We also learned that adoption of improved maize varieties only, led to the highest maize yields and this probably because of the high response rate of improved maize to inorganic fertilizers. On the other hand, adoption of more than one SAP resulted in more income, compared to those adopted in isolation. Similar results were obtained in Ethiopia (Teklewold *et al.,* 2013b) and Malawi (Kassie *et al.,* 2014c). In Ethiopia, the authors analyse the impact of adopting three interrelated SAPs (maize-legume rotation, improved maize seed and minimum tillage) on several outcome variables. They find that the combination of all three SAPs provided the highest maize income as compared to the case when the SAPs were adopted individually. Similarly, in Malawi, Kassie *et al.* (2014c) found that when farmers adopted improved maize varieties with minimum tillage, they realized higher yields than when these two practices were adopted in isolation. The findings in this thesis are important because it is indisputable that food production in the coming years will have to increase to meet the increasing demand for food (Godfray *et al.,* 2010; World Bank, 2008; Tilman *et al.,* 2002). However, increasing agricultural production comes with it some externalities that maybe harmful to the environment (Tilman *et al.,* 2002; Pretty, 2008). The challenge therefore is to increase agriculture production, but at the same time reduce the adverse effects that agriculture may impact on the environment. The results of this thesis have shown that the promise in this area may lie in the use of sustainable agricultural practices (SAPs).

7.3 Can improved agricultural technologies sustainably improve farmer's welfare?

There is no doubt that the adoption of improved agricultural technologies (in this context improved maize and SAPs) is important in improving the welfare of smallholder farmers, especially in the agricultural based communities. Many researchers agree that improved agricultural technologies are superior to traditional technologies in terms of both yields and incomes (e.g.Alene *et al.,* 2009; Arslan *et al.,* 2015; Mathenge *et al.,* 2014a). The results from chapters 3 to 6 also show that adoption of improved agricultural technologies is essential in improving the welfare of smallholder farmers in Zambia. Although mining is the most important sector in Zambia, the results from this thesis clearly show that agriculture can be one of the sustainable pathways through which income, food security and child malnutrition can be improved. Improved maize adoption can also help farmers increase their assets as income is accumulated and capitalized (Smale and Mason, 2014), which makes farm households more resilient to shocks over time.

However, improving farmer's welfare is one thing and doing so sustainably is another. This is because the adoption of improved agricultural technologies goes along with some investments such as the purchase of seed and fertilizers which may be expensive for some small scale farmers to afford. It was evidenced by all chapters that adopters of improved agricultural technologies were better off, even prior to the decision to use these technologies, pointing to the issue of selection bias (self-selection)[33]. This implies that very poor farmers may not adopt these technologies because of cash constraints. In such a situation, doubts have been cast on whether

[33] This partly justified the use of IV based methods.

improved maize adoption can increase famer's income on a sustainable basis especially for poor marginalized farmers. In response to this, the Government of Zambia (GoZ), through the FISP and FRA has participated in both output and input markets. The objective behind FISP for instance is to improve household and national food security, incomes, accessibility to agricultural inputs by small-scale farmers, and to 'build the capacity of the private sector to participate in the supply of agricultural inputs' (MACO, 2008). Although the programme has been credited for the increase in the adoption of improved maize varieties, the impact of this program with regards to raising incomes and reducing poverty amongst poor farmers has been minimal (Mason and Smale, 2013) and one reason for this is that the FISP has mainly concentrated on increasing the maize productivity among smallholders and not poverty reduction *per se* (Smale *et al.*, 2014). It is also clear that continued provision of these subsidies may not be sustainable in the near future. In light of these difficulties, results in this thesis offer some promising solutions to these problems.

The implication from the results in chapter 6 is that improved maize varieties are crucial in raising the productivity of maize. However, because of the costs involved in improved maize adoption, highest incomes were observed when other soil fertility enhancing technologies were applied on the maize plots. This essentially has a direct implication on the poor smallholder farmers who are missed out on national programs such as FISP. The adoption of improved maize varieties, along with the soil fertility enhancing SAPs clearly reduces the application of fertilizers, which is the most costly input in the production of maize in landlocked Zambia. SAPs are therefore an important link through which sustained maize yields, incomes and lower poverty levels can be attained. In the current setting in Zambia, maintaining the welfare gains based on the adoption of improved maize only may not be very feasible without the accompanying SAPs.

7.4 Policy implications

Arising from the results and discussion above, important policy recommendations can be drawn. First, it is important that adoption of improved maize varieties continues to be encouraged, especially among the resource poor farmers as it has been shown to be beneficial to not only adopters, but to potential adopters also. One vehicle that has contributed to the adoption and diffusion of improved maize is the FISP and although no detailed treatment has been given to input subsidies in this thesis, extensive literature on this subject exists in Zambia (e.g. Mason and

Smale, 2013; Smale *et al.,* 2014). To help in lifting of farmers out poverty, there is consensus among researchers that the FISP should be reorganized so that it more oriented to targeting the poor famers than the way it is being currently implemented. Unsustainable as the programme may be, it may be one of the ways in which farmers can build their capital base, which in the long run can help the farmers stand on their own.

Second, literature on SAPs in Zambia shows that there is both low adoption and high levels of dis-adoption of these practices by smallholder farmers (Andersson and D'Souza, 2013; Arslan *et al.,* 2013). The challenge therefore is the promotion and realization of widespread and durable adoption of SAPs (Arslan *et al.,* 2013). Arising from this thesis is a dire need for more investment in education for the farmers to understand and appreciate the benefits (e.g. pest control, droughts etc.) of these SAPs as it has been shown in this thesis. With the ever increasing threat of climate change, SAPs will become an important part of the farming systems to mitigate the adverse effects of climate change (Arslan *et al.,* 2013).

Third, it was mentioned in chapter 2 that Zambia has three agro-ecological regions which receive different amounts of rainfall. Results in chapter 6 revealed that a combination of two SAPs (improved maize and residue retention) led to the highest income results and this pertained to the agro ecological region II which is the middle rainfall area. It is possible that a different combination of these practices maybe the most beneficial in the other regions, hence it is important that extension agents and farmers find a suitable mix of these SAPs that will be most appropriate in their region.

7.5 Critical reflection and further research

7.5.1 Critical reflection

To distinguish between correlation and causality, is one the most difficult challenges faced by empirical researchers in the social sciences (Altonji *et al.,* 2005). The challenge is more daunting when it comes to isolating impacts or causal effects attributed to a particular intervention such as improved agricultural technologies. In this thesis, we applied a number of assumptions and methodologies in order to attach a causal interpretation to our results and as such questions relating to the validity of the results may arise. Others may also question the external validity of the results in this thesis as they pertain only to Zambia.

In chapters 3, 5 and 6, we assumed selection bias resulted from both observables and unobservables as such we used the exclusion restriction assumptions to identify our models. In addition to the difficulties encountered in finding a valid instrument (Angrist and Krueger, 2001), the models in these chapters also imposed distributional and functional form assumptions. In light of these difficulties, can the results of these chapters be trusted? I think so for two reasons. First, it is important to admit that finding an instrument that is perfect is almost impossible. However, we tried to select valid instrument by using detailed information from the economic and adoption literature. For instance, theory suggests that farmers would adopt a particular technology based on the costs and benefits relative to the older technology (Feder *et al.*, 1985). Hence one possible source of instruments would be the transaction costs associated with adopting a new technology (e.g. distances to the input markets and extension agent's office). Second, to build more confidence in our results, in all chapters we also estimated the well-known PSM method, which relies on the unconfoundedness assumption as a robustness check. Even though the magnitudes of the estimates differ (which is expected because of the different assumptions), the conclusions from the PSM methods are exactly the same as those from the IV based approaches.

Another source of concern that may result from this thesis maybe the definition and measurement of the outcome variables used in the analyses, including the measurement of household income/expenditure (chapters 3, 4, and 6), and subjective food security measures (chapter 4). The income and expenditure data was collected during a one round survey from the head of the household, who was presumed to be knowledgeable about the household expenses and income using recall method. This raises the possibility of having inaccurate information and nonresponses because it is possible that individuals may report only their expenses and forget about the expenses of other household members (Browning *et al.*, 2014). Although it is almost impossible to correct for all the errors associated with income/expenditure measurement, we tried to control for this by recording both income and expenditure. In an ideal situation, the income and expenditure data should be almost the same and in our case, these variables were similar in term of magnitude. Experienced, seasoned interviewers were also used when collecting the data to ensure high data quality. Self-reported food security measures usually elicit responses by raising potentially emotive subjects, such as hunger, anxiety or general well-being and in doing so induce response biases (and in unpredictable directions) (Headey and Ecker, 2013).

Despite these potential problems, Headey and Ecker (2013), show that there is a relatively strong correlation between subjective measures and household expenditure. Additionally they also mention that the cost of capturing these measures is quite low, and they can also capture seasonality through questions such as the “number of month of hunger experienced in the last year”. These types of questions were included in the questionnaire used in this thesis. By comparing the subjective to objective measures, we contributed to the understanding of how best food security can be measured, especially at household level.

Finally how applicable are the results to the southern African region? It is no doubt that agriculture in most of the economies in southern Africa is one of the most important sectors and maize in particular is the most important food crop (Smale and Jayne, 2003). Similarly, since most of the countries in this region are maize based, SAPs based on conservation agriculture principles have also been widely promoted in the region (Andersson and D'Souza, 2013). Coupled with this, the climatic conditions experienced in Zambia are similar to most countries in the region. Based on these reasons, the results from this thesis can generally be applied to most of the countries in the region.

7.5.2 Further research

Previous studies in Zambia have shown that there is a lot of heterogeneity within the smallholder maize grower’s population (Smale and Mason, 2014). There is also a wide range of variability with regards to the smallholder maize production as well as incomes over time. Disentangling the dynamics relating to this heterogeneity requires studying the behavior of farmers over a period of time. It was impossible to do this in this thesis because of the data limitations as data was collected in a single round of survey. The use of panel data may help in mitigating some of these problems. First, panel data allows one to fully understand the dynamics with regard to the determinants of technology adoption as individuals are followed up overtime. Second, even though methodologies that account for selection bias and endogeneity were used in this thesis, finding a suitable instrument that is correlated with treatment variable and uncorrelated with the outcome variable is always a challenge. Panel data models can help to get round this problem because lagged values can be used as valuable instruments. With regards to SAPs, panel data may help researchers gain more understanding on the impact of these practices on the soil and environment over a period of time.

Child malnutrition is a very a complex issue which is influenced by many multidimensional factors (Jesmin *et al.,* 2011). Understanding how agriculture affects the nutritional status of children is even a more unnerving task. In chapter 5, this relationship was tested by mainly looking at the income pathway and not through the diet composition pathway. As Zeng *et al.* (2014) mentions in their study, the consumption of maize had the highest nutrition effects. However they do not qualify whether what was being consumed was improved maize with high protein content or vitamin A enriched maize. Future studies could look at both the income and diet composition pathway through the use of dietary diversity indicators. Headey and Ecker (2013) show in their study that the dietary diversity indicators were highly correlated with child nutrition indicators. This would build more confidence in the resulting estimates on malnutrition. Efforts should also be made to collect more detailed information with regards to the protein content of the improved maize varieties that are being consumed by the rural populace. Studies that will look at establishing a link between adoption of improved varieties and child malnutrition should also try to control for the consumption of other nutritious products such as meat, beans, soybeans, etc., in the nutrition production function such that the resulting outcome should solely be attributed to the adoption of such varieties.

One area of research that has not received a lot attention in the adoption and impact literature is the dis-adoption and non-adoption of agricultural technologies. Further research, especially using panel data should analyse the dynamics behind the dis-adoption and non-adoption of technologies. This is especially important for SAPs where high levels of dis-adoption are often reported. Understanding why some farmers dis-adopt SAPs for instance may help researchers to develop suitable packages that meet the needs of the farmers.

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SUMMARY

This thesis evaluates the adoption and impacts of improved maize varieties and sustainable agricultural practices (SAPs) on the welfare of smallholder farmers in the Eastern province of Zambia. Although a considerable number of households have adopted these improved agricultural technologies, evidence on the welfare effects of these technologies is still limited in Zambia. This thesis is an attempt to fill this gap.

Chapter 1 discusses how agriculture can be linked to the general well-being of farm households and to the global goal of sustainable development. This chapter sets the stage and motivation for conducting the research presented in this thesis. The chapter also presents the specific research objectives for this thesis and highlights the key methodological approaches employed in meeting these objectives.

Chapter 2 presents the characteristics of the study area including the agro-ecological regions and socioeconomic activities. Details on the sampling procedure as well as the districts in which the household survey was conducted are also given. The chapter concludes with a brief description of the survey data and main variables used in the thesis.

Chapter 3 to 6 form the principal part of the thesis. In chapter 3 the objective is to unravel the determinants of improved maize adoption and the impact of these varieties on the welfare of smallholder farmers. This chapter concludes that education, access to extension, membership in cooperative group, asset ownership, access to information on improved maize varieties and markets have a positive effect on adoption of improved maize varieties. The results also show that improved maize adoption has a positive effect on the indicators of well-being, i.e. income, expenditure, and poverty. The results further show non-adopters would have had higher incomes, expenditure, food security and lower levels of poverty, had they switched from growing local to improved maize varieties.

In chapter 4 we analyse the impacts of improved maize adoption on the food security status of farm households. To achieve this objective, we use both objective and subjective food security measures in analyzing the relationship between improved maize adoption and food security. The chapter also makes a methodological contribution with regards to obtaining robust estimates when specifying empirical models for impact evaluation. The conclusion in this chapter is that adoption of improved maize varieties leads to an improvement in food security based on both the subjective and objective food security measures. The outcomes based on

objective food security measures were higher than the subjective measures and this can be attributed to the fact that the food expenditure measure may be prone to either under- or overestimation. The other conclusion from this chapter is that since no single measure of food security may be deemed as the best, it is important that multiple measures of food security (objective and subjective) be used in explaining the impact of new agricultural technologies adoption (including improved maize).

In chapter 5 we examine the determinants of child nutritional status and the impact of improved maize on child malnutrition. The results from this chapter show that, depending on whether children came from improved maize adopting or non-adopting households, factors affecting child nutrition are different. With regards to the impact of improved maize adoption on stunting, the results show that improved maize adoption reduces the probability of stunting. This implies that improved maize not only improves welfare and food security of farm households (as shown in chapters 3 and 4), but goes beyond to improve child malnutrition. The counterfactual analysis also shows that children from non-adopting households would have realized lower rates of stunting had their parents adopted improved maize.

In chapter 6, we investigate whether SAPs adopted in isolation resulted in higher benefits than those adopted as a package. The SAPs in question include residue retention, maize legume rotation and improved maize. To achieve this objective, we combined household with plot level data. From this chapter it can be concluded that improved maize varieties when adopted in isolation result in the highest yields, however, because maize requires a lot of inputs such as fertilizer, adopting a combination of maize-legume rotation and residue retention results in the highest household income. This is an important finding because most farmers in the rural areas of the Eastern province are poor and cannot afford to purchase fertilizers; hence promoting the adoption of SAPs among these households can greatly help in improving their incomes and consequently food security.

Overall the results from this thesis show that the adoption of improved agricultural technologies important in improving the welfare of smallholder farmers. Chapter 7 gives a synthesis of the results and discusses their implications. It also gives a critical reflection on the work that was done in this thesis and provides avenues for further research.