Using robust identification strategies to evaluate impact of 2010/2011 farmer input support programme on maize yields and asset accumulation in rural Zambia

By

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DECLARATION

I, *Edward Mambwe Chibwe,* hereby declare that the dissertation, which I hereby submit for the degree of *MSc Agricultural Economics* at the University of Pretoria, is my own work and has not previously been submitted by me for a degree at this or any other tertiary institution.

Signed by: ______________________

Name: EDWARD M. CHIBWE

July 2014

DEDICATION

To my parents, Moffat and Angelina Chibwe

To my wife Lubasi Sinyinda Chibwe, my daughter Besa Mbuyoti Chibwe, and my son Siyumbwa Chibesa Chibwe

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ABSTRACT

The Zambian government, through the Ministry of Agriculture and Cooperatives (MACO), provides maize seed and fertilizers to farmers at heavily subsidised prices under the Farmer Input Support Programme (FISP). MACO's narrow evaluation of FISP, based on estimated production without quantifying the significant changes in production and other critical socioeconomic factors, fails to adequately highlight and service the benefits of subsidies to intended beneficiaries. Furthermore, MACO estimates of the impact of FISP never consider the question of how much beneficiary farmers would have produced in its absence, leading to potentially misleading assessments. The key question addressed in this study is whether using more rigorous econometric methods that account for heterogeneity in socioeconomic factors between participants and non-participants would still confirm the positive impact of FISP on maize productivity and poverty reduction, hence justifying the huge government expense on the programme. The study utilised cross-sectional data obtained from 497 randomly selected households, collected in 2011 from six provinces of Zambia to assess the causal effect of FISP on beneficiary households' maize yields and asset accumulation. The data was analysed using well-grounded matching techniques that account for differences in observable characteristics between programme participants and non-participants. The study also tested for possible unobserved selection effects using the Rosenbaum bounds. The results indicated that participating in FISP increased maize yields and assets accumulation and hence might directly or indirectly positively affect beneficiary poverty levels. There were also no influences of unobserved characteristics on the estimated maize yield and asset level differences between participants and non-participants. On average, FISP increased maize yields by about 451 kg per hectare, with an improvement of about 0.5 on the wealth index (score used to rank households according to asset levels). The positive impact on maize yields and asset accumulation on the participating farmers therefore justifies government's continued implementation of FISP.

Keywords: Farmer Input Support Programme participation, maize yield, asset accumulation, poverty reduction, impact evaluation, propensity score matching, Zambia

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LIST OF ABBREVIATIONS AND ACRONYMS

3ie	International Initiative for Impact Evaluation
ACF	Agricultural Consultative Forum
AEZ	Agro-Ecological Zone
ATT	Average Treatment on the Treated
CBOs	Community-Based Organisations
CIA	Conditional Independence Assumption
CIMMYT	International Maize and Wheat Improvement Centre
CSO	Central Statistical Office
DAC	Development Assistant Committee
DASP	Distributive Analysis Stata Package
ESR	Endogenous Switching Regression
FAO	Food Agriculture Organisation
FGT	Foster-Greer-Thorbecke
FISP	Farmer Input Support Programme
FSP	Food Security Pack
FSRP	Food Security Research Project
GDP	Gross Domestic Product
IITA	International Institute of Tropical Agriculture
IMF	International Monetary Fund
IV	Instrumental Variable
LCMS	Living Conditions Monitoring Survey
MACO	Ministry of Agriculture and Cooperatives
MFNP	Ministry Of Finance and National Planning
NN	Nearest Neighbour
OECD	Organisation for Economic Cooperation and Development
PCA	Principal Component Analysis
PDA	Personal Digitalised Assistance
PRSP	Poverty Reduction Strategy Programme
PS	Priority Survey
PSM	Propensity Score Matching
PWAS	Public Welfare Assistance Scheme
ReSAKSS	Regional Strategic Analysis And Knowledge Support System
SEA	Standard Enumeration Area
SSA	Sub-Saharan Africa
ToC	Theory of Change
UNDP	United Nations Development Programme
US$	United States Dollar
USAID	United States Agency for International Development
ZDA	Zambia Development Agency
ZNFU	Zambia National Farmers' Union

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND TO THE STUDY

The government of Zambia, like those of most Sub-Saharan countries, has been focusing on improving rural incomes, agricultural production and the productivity of rural smallholder farmers growing mostly staple crops like maize. To achieve this objective, input subsidies have been used as a policy tool to induce farmers to increase their yields through increased use of hybrid seed and chemical fertilizers (Chibwana, Fisher & Shively, 2011; Ricker-Gilbert, Jayne & Black, 2009). This policy was introduced in 2001 as a transitory measure and was dubbed the Farmer Input Support Programme (FISP)[1]. FISP was initially designed to be a four-year programme meant to contribute to improved household and national food security, by improving smallholder household access to quality inputs, in addition to helping them to recover from the losses in their asset base due to adverse weather conditions experienced during the 2001/2002 agricultural growing season.

FISP targets all smallholder farmers capable of cultivating at least one hectare of maize, provided they can pay 50 % of the full market price of inputs and are active members of any approved or registered farmer organisation. The programme provides a standard input pack[2] of 10 kg of maize hybrid seed and 100 kg each of basal and top dressing fertilizers sufficient for the cultivation of a half hectare of maize to all its beneficiary farmers. The distribution is through registered agricultural cooperatives, farmers' associations and/or farmer organisations. Each beneficiary farmer is allocated one pack of inputs and must not concurrently benefit from other similar government programmes like the Food Security Pack, which is a programme designed to provide

[1] FISP was formerly known as the Fertilizer Support Programme (FSP). The name change has not affected the programme's initial objectives, but has only changed its implementation modalities. Therefore, in this paper, FSP and FISP are considered to be the same programme.

[2] In the seasons preceding the 2009/2010 agricultural season, the standard pack was double the current one to support one hectare of maize production (i.e. 20 kg seed + 4x4 fertilizers).

inputs to smallholder farmers too poor to purchase fertilizer and seed, even at subsidised prices (MACO, 2009; World Bank, 2010).

FISP is the single largest and most significant agricultural input subsidy programme in Zambia, as indicated by the national budget allocated to it, which shows a strong positive trend, recording phenomenal growth of 16 % per year over the past decade. It consumes approximately one third of the budget of the Ministry of Agriculture and Cooperatives (MACO). The programme also accounts for roughly 45 % of the optional budget for poverty reduction programmes (Bigsten & Tengstam, 2009; World Bank, 2010).

In Africa, and indeed most developing countries, governments have been struggling for decades with the problem of assessing and justifying expenditure on subsidy programmes. For example, spending by the Zambian government on subsidies for a target of 120 000 farmers for the 2002/2003 agricultural season was about US$ 20 million (ZMK 100 billion), while for a target of 200 000 farmers in the 2008/2009 agricultural season, spending was US$ 98 million (ZMK 492 billion) (MACO, 2009; World Bank, 2010). Correspondingly, in the past decade, Zambia has recorded increased national maize yields, increasing on average from about 1 366 kg/ha in the 2005/2006 agricultural season to about 2 125 kg/ha in the 2010/2011 agricultural season – a 55 % increase. This was mostly accounted for by the increase in maize yield between the baseline period and the 2011 harvest, rather than expansion in the area planted to maize (less than 30 %) (Mason, Burke, Shipekesa & Jayne, 2011).

Programmes such as FISP can be evaluated using several criteria, but always taking into consideration the question of the programme having achieved its intended objectives and to what extent. Most impact evaluations focus on four major aspects, calculating various indicators for each aspect, namely economic development, input market, impact on programme characteristics, and production. To provide a comprehensive picture of the effectiveness of the programme, the evaluation needs to use as many indicators as possible (Tiba, 2009).

In Zambia, MACO uses estimated increases in production and productivity as evaluation indicators, which fall on the aspect of production. This approach is rather limited, as it does not take into account other important factors that might influence smallholder farmer production and productivity such as response to the Food Reserve Agency (FRA)[3] floor price signals, weather and seasonal conditions. Furthermore, MACO estimates of the programme's production have also overlooked the question of how much maize the beneficiary farmers would have produced without the programme (World Bank, 2010). Therefore in this study, to complement MACO's efforts and thus provide robust insights regarding FISP's impact in Zambia, the programme was subjected to a rigorous econometric evaluation using a quasi-experimental method.

Often, agricultural productivity and welfare improvements in terms of asset accumulation go hand in hand, but sometimes they do not. Large divergences between productivity and asset accumulation may arise when productivity is volatile and unsustainable. The question is, can such divergences between productivity and asset accumulation still arise when agricultural productivity is sustained? It is also assumed that rural households are said to be poor mainly due to low levels of assets in their possession, as well as limited earnings of returns from these assets, leading to an inability to accumulate further assets. Looking at the assets of the programme's intended beneficiaries is thus essential in understanding poverty dynamics and addressing the constraints that prevent poor rural farmer households from improving their productivity (Chronic Poverty Advisory Network, 2012). In this study, asset accumulation using a wealth index as a proxy moves it even further by connecting various forms of assets to the household livelihood strategies and thus poverty levels.

The study used Propensity Score Matching (PSM) to assess the impact of FISP on agricultural yield and asset accumulation from cross-section data collected for a maize baseline survey in 2011. FISP was designed as a targeted programme with the intended beneficiaries selected on the basis of a prescribed eligibility criterion, although in most instances this has been ignored to satisfy recurrent political ambitions (World Bank, 2010). PSM is a non-parametric procedure and avoids the restriction involved in models that require the relationship between characteristics and outcome to be specified. Also, in using PSM, it is assumed that FISP selection can be explained purely in terms of observable characteristics. Accounting for unobserved units in such programmes is also important, as inaccurate targeting and selection (selection bias) of

[3] Currently FRA is the largest maize buyer in Zambia for both strategic reserves and buyers of the last resort, and together with government sets the floor price for maize.

intended beneficiaries has been pronounced due to bias on the part of the organisations that are given the mandate to select FISP beneficiaries. Use of cross-sectional data gives the study an additional advantage to use a matching procedure to minimise the unobserved heterogeneity biases. As stated by Hall and Maffioli (2008), any assessment of the impact of a subsidy programme cannot be justified by looking at different periods or time series, but rather by creating a counterfactual within the same period so as to reduce the potential selection bias by utilising the same dataset to create a control group. Therefore, to check whether the FISP participation effect is sensitive to unobserved selection bias, the study used the Rosenbaum bounds procedure, as well as endogenous switching regression.

1.2 PROBLEM STATEMENT

Agricultural subsidies not only keep the costs of inputs to poor farmers low and affordable (Eboh, 2006), they raise farmers' incomes, reduce food prices and poverty, and promote economic growth through an increase in agricultural productivity or input use (Crawford, Kelly & Jayne, 2003; Garcia, 2007).

Despite all the positive results that have been shown by FISP towards achieving the national food production objectives, the programme is still being heavily criticised. Moreover, the total size of FISP as a single-subsidy programme and its level of assistance have been allowed to fluctuate and grow, instead of seeing a systematic reduction (by 25 %) in programme support each year as originally planned, leading to the creation of uncertainty for farmers and other stakeholders. In terms of priority ranking in the Fifth and Sixth National Development Plans (FNDP and SNDP) for Zambia, FISP is ranked lower than investment in irrigation development, livestock development, agricultural infrastructure and land development, but it still receives more resources than the highly ranked programmes (MoFNP, 2011; Petrauskis, 2007; World Bank, 2010).

Since FISP's inception, many questions have been raised about the programme's actual achievements and effectiveness in increasing agricultural productivity, improving beneficiaries' welfare and consequently reducing poverty (World Bank, 2010). It is also apparent that the empirical performance of FISP in Zambia is uneven, incomplete and not very comprehensive, showing variations across and within provinces (FSRP & ACF, 2009).

Given the importance of agriculture to Zambia and the high level of spending on FISP to date, it is notable that apart from a review of the programme to improve its implementation and an analysis of its effectiveness and efficiency, no studies have been done in Zambia to specifically and affirmatively confirm the apparent positive effect of the programme's contribution to agricultural productivity and other national priorities such as rural poverty reduction.

Therefore, to justify such programmes targeted at improving food production and welfare, there is a need to use more rigorous econometric methods that will account for heterogeneity in socioeconomic factors between participants and non-participants.

1.3 OBJECTIVES OF THE STUDY

The aim of the study was to assess the impact of participation in the 2010/2011 FISP on household maize productivity (yield) and welfare (asset accumulation) in Zambia's agro-ecological zones II and III using a quasi-experimental econometric approach.

The study was aimed at achieving the following specific research objectives:

1. To estimate the impact of FISP on smallholder farmers' households' maize yields;
2. To estimate the impact of FISP on smallholder farmers' asset accumulation; and
3. To deduce the effect of FISP on poverty reduction.

The above objectives therefore allowed the study to investigate the following null and alternative hypotheses:

H_0: There is *NO* difference in maize yields and asset accumulation between FISP beneficiaries and non-FISP beneficiaries.

H_1: There *IS a* difference in maize yields and asset accumulation between FISP beneficiaries and non-FISP beneficiaries.

H_0: There is *NO* difference in poverty levels between FISP beneficiaries and non-FISP beneficiaries.
H_1: There *IS a* difference in poverty levels between FISP beneficiaries and non-FISP beneficiaries.

1.4 ACADEMIC VALUE AND INTENDED CONTRIBUTION OF THE STUDY

Determining the impact of FISP in Zambia where the government has continued to allocate huge financial resources at the expense of important national priority developmental programmes would definitely assist policy makers in designing appropriate policy intervention.

This study may also support national policymakers and other agricultural stakeholders by providing empirical, robust results needed for meaningful and transparent deliberations on the current and future role of input subsidies in developing countries.

This study, being the first of its kind in Zambia to compare the yield and asset accumulation of FISP participants and non-participants using more rigorous econometric methods, will advance the literature on the impact assessment of subsidy programmes and thus assist researchers interested in the effect of agricultural subsidies on small-scale farmers.

1.5 LIMITATIONS AND ASSUMPTIONS ADOPTED IN THE STUDY

This section discusses the boundaries and assumptions of the study.

1.5.1 Study Limitations

Firstly, the study assumed that the control and treatment groups were highly comparable based on the fact that cross-sectional data was used and individuals were drawn from similar agro-ecological areas. Therefore, the more the data diverged from this assumption after trimming to the common support requirement in estimating the propensity scores, the more biased would be the estimators thus obtained.

Secondly, the PSM procedure can only eliminate the selection biasness of exogeneity if the model is correctly specified and the confounding covariates properly measured; but since the propensity score could only be modelled with respect to observed covariates that are balanced, it is not certain that the propensity score also balances the unobserved covariates. This means that if unobserved covariates are correlated to observed factors, the limitation is modified; otherwise large sample sizes might be needed in order to establish adequate variance in covariate distributions.

Thirdly, it is noted that the study would be overstretching the impact of FISP if the programme were directly linked to poverty reduction in the absence of a benchmark; therefore the study attempted only to compare the poverty levels of the FISP participants and non-participants during the 2010/2011 agricultural season.

Lastly, since a finite sample of 497 was used, notwithstanding precautionary measures in mitigating bias due to the type of method used, the PSM procedure was at risk of suffering from finite sample bias due to the lack of exact matches.

1.5.2 Study Assumptions

For this study to achieve its stated objectives, certain assumptions were made. Firstly, the study assumed that the selected unit of observation, the household and the variables thus collected from them were sample statistics and thus estimated the true population parameters with the same error.

Secondly, the cultural tradition limitation of disclosure of information such as consumption expenditure, income or assets did not affect the data collection process.

Thirdly, to allow for comparisons across households, the households were assumed to be sufficiently similar – that is, the FISP non-beneficiaries (untreated) were assumed to resemble the FISP beneficiaries (treatment) in every way, with the only difference between them being their programme participation.

Finally, since the study used an existing dataset and recognised that matching techniques were sensitive to the number of observations available, it was assumed that to guard against the study's use of a small sample size, especially of the untreated, the use of several matching algorithm techniques could go some way towards minimising the sensitivity associated with a finite sample size, although a large sample size would have been more ideal. Furthermore, as stated above, it was assumed that the untreated group was highly similar to the treatment group, hence there was no need to increase the size of the control units, as most of the treated would overlap in common support with any of the controls.

1.6 DEFINITION OF KEY TERMS

The key terms used in this study are defined in **Table 1** below.

Table 1: Definitions of key terms

Key term	Definition
Asset	An asset is identified as a "stock of financial, human, natural or social resources that can be acquired, developed, improved and transferred across generations. It generates flows or consumption, as well as additional stock" (Ford, 2004).
Food security	For purposes of this study, the definition of food security as given by the World Food Summit held in 1996 (FAO, 1996) is used, as it forms the basis of all current definitions of food security: "Food security exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life."
Incidence of poverty (headcount index)	The Incidence of poverty (headcount index) is defined as the share of the population whose income or consumption is below the poverty line, whereas the poverty gap (depth of poverty) measures how far off households are from the poverty line. This measure captures the mean aggregate welfare indicator shortfall relative to the poverty line across the whole population (Van Domelen, 2007).
Household	CSO (2012) defines a household as a group of persons who normally live and eat together.
Input subsidies	Input subsidies, which are the focus of this study, refer to direct financial support provided by different levels of government to input industries, parastatal and private input traders and farmers. To farmers, subsidies are designed to increase their production directly and they often have immediate and short-run effects (Fan, Gulati & Thorat, 2008).
Poor	The poor are those who do not have enough income or assets to put them above some adequate minimum threshold (World Bank, 2000).
Poverty	Poverty is defined by the World Bank (2000) as pronounced deprivation in wellbeing

Key term	Definition
Poverty line	A poverty line can be defined as the minimum welfare indicator required to fulfil basic needs or the threshold consumption needed for a household to escape poverty. The poverty line has been seen to be somewhat arbitrary, because the line between the poor and non-poor can be hard to define (Haughton & Khandker, 2009).
Pro-poor programme	Van Domelen (2007) termed a programme as pro-poor "if the incidence of the programme beneficiaries or resources going to the poor is more than their relative share in a given population or simply programmes in which the poor are overrepresented".
Smallholder farmer	Smallholder farmer is a term that refers to both small- and medium-scale farmers that produce for household consumption using low levels of technology, who tend to sell the surplus produce and cultivate land between 0 and 20 hectares (MACO, 2009).

1.7 ORGANISATION OF THE THESIS

This thesis is divided into seven chapters. Chapter 1 provides the study background, problem, purpose statements and objectives of the study, including the limitations and assumptions used in the study and the definition of key terms used. Chapter 2 provides a review of agriculture in general, the poverty situation and interventions used in Zambia. Chapter 3 reviews the literature on impact assessments and Chapter 4 discusses impact evaluation methods and their application. Chapter 5 looks at the research design adopted in the study, the data collection procedure and characteristics of the sampled households. Chapter 6 presents the results and discussion thereof. Chapter 7 gives the conclusion and policy implications of the study.

CHAPTER 2

REVIEW OF ZAMBIAN AGRICULTURE, POVERTY SITUATION AND GOVERNMENT INTERVENTION

2.1 INTRODUCTION

This chapter tackles the general agricultural and poverty situation in Zambia, looking at the position and significance of agriculture, as well as the various interventions that have been used to improve the agricultural sector in Zambia. The last part of the chapter looks specifically at the location and position of the study area.

2.2 AGRICULTURE IN ZAMBIA

The Zambian economy is largely agriculturally based, with the sector's average contribution to Gross Domestic Product (GDP) standing at an average of 18 % over the past decade. Agricultural output in Zambia increased from 18 % of GDP in 2008 to about 20 % of GDP in 2009 as a result of increased area planted, good rainfall patterns across the country, as well as favourable agricultural policies by government (ZDA, 2011).

In 2010, the agricultural sector grew by 7.8 %, with the largest contribution made by maize. The growth projections for 2011 and 2012 stood at 3.2 % and 4.6 % respectively (African Economic Outlook, 2011; CSO, 2011).

According to the monthly report for June 2010 released by CSO (2011), Zambia's total population from the 2010 census was recorded at slightly over 13 million, with over 75 % of the population deriving its livelihood from agriculture and its related activities. Agriculture in Zambia is therefore regarded as one of the driving forces for economic growth in its National Development Plans (NDPs). It is therefore the government's core strategy for rural development (MoFNP, 2006) and could be enhanced by either combining the promotion of appropriate technologies with the subsidy programme or investments in farmer extension support and education programmes.

2.2.1 Position of agriculture in Zambia

Agriculture in Zambia is mainly confined to subsistence and small-scale (growing for both subsistence and the market) farming. The majority of these smallholders are asset poor and use simple technologies (hand hoes and oxen), conventional cultivation practices and minimal purchased inputs such as hybrid seed or fertilizer (Siegel, 2008).

The agricultural sector is largely dependent on rainfall (which is influenced by seasonal weather patterns) and the utilisation of non-sustainable agricultural practices such as shifting cultivation and mono cropping. These practices are reflected in the declining agricultural productivity, which has also been exacerbated by several factors including soil degradation, poor access to inputs, utilisation of new but inappropriate technologies, and low investment in agricultural research, training and extension services, along with inadequate access to agricultural service support, especially credit (MACO, 2009).

It is for this reason that the Poverty Reduction and Strategic Paper (MoFNP, 2002) and Fifth National Development Plan (MoFNP, 2006) for the country acknowledge that for the majority of Zambians to escape the poverty trap, there is a need to improve agricultural production, productivity and market competitiveness.

2.2.2 Significance of agriculture in Zambia

The importance of agriculture in Zambia is accentuated by the budgetary allocation to the sector both before and after the Maputo Declaration[4] on agriculture (AU, 2003). As indicated in **Figure 1**, the national budget allocation to agriculture increased by an average of 7 % between 2004 and 2011 – higher than most African states. The World Bank (2010) noted that the agricultural sector's actual share of the national budget has been increasing significantly, even surpassing the 10 % Maputo Declaration threshold. For example, in the period 2000 to 2008, the agricultural share rose from 7.4 % to 12.5 %, although the percentage dropped during 2010 and 2011 (Curtis, 2013).

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[4] The Maputo Declaration, signed by African Union members in 2003, entailed the signing countries committing a share of 10 % to agricultural expenditure by 2008.

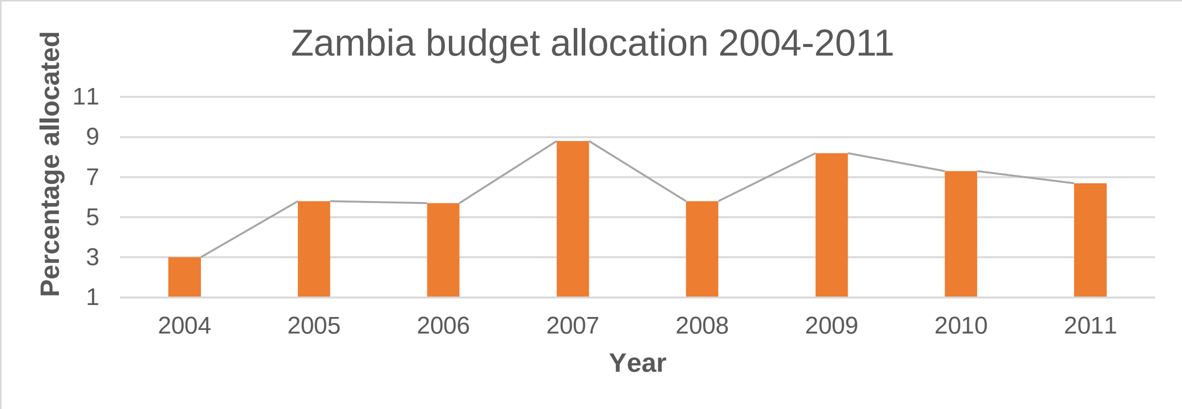


Figure 1: Zambian government's budget allocation to agriculture (without FISP and FRA)
Source: Curtis (2013)

2.2.3 Government intervention in agriculture

Agriculture-led growth is likely to provide the most benefits for Zambia's poor and the wider economy. Increased and better investments in agriculture are therefore critical (Curtis, 2013). Prior to 1990, the agricultural policies were restrictive, distortionary and counterproductive due to heavy government intervention and participation, along with the dominance of maize and these policies being regarded as unsustainable due to their heavy reliance on subsidies. Maize is Zambia's principal crop and accounts for over 70 % of the total value of smallholder crop production. The agricultural sector also lacked private sector participation in the areas of agricultural marketing, input supply and processing. Policies distorted the allocation of resources away from crops in which Zambia has a comparative advantage and created a growing and unsustainable burden upon the government budget (Jayne & Govereh, 2007).

In 1991, the government embarked on a process of agricultural sector policy reforms, which were part of the overall economic reforms pursued under the Structural Adjustment Programme (SAP). The main policy thrust of the reforms was the liberalisation of the agricultural sector and the promotion of private sector participation in the agricultural value chains, but the performance did not match expectations due to a number of constraints, including limited resources (World Bank, 2010).

Although such liberalisation policies were promoted in the 1990s, agricultural subsidies – especially fertilizer subsidies – have remained important in Zambia. This became apparent after the country experienced serious drought conditions in the 2001/2002 growing season, which accentuated increasing poverty levels and falling proportions of maize being grown by smallholder farmers due mainly to a lack of, or inadequate access to, inputs. A policy instrument that included pan-territorial pricing (same price everywhere) and pan-seasonal pricing (setting a floor price) was therefore adopted, along with 50 % subsidies for fertilizer and transport to encourage maize production, especially in remote regions where the majority of the poor are assumed to live (Govereh & Shawa, 2006).

Such subsidies are aimed at addressing the social and political objectives of poverty reduction and improving food security. Some economists argue that input subsidies have political appeal, with most African governments – including the Zambian government – choosing to implement such subsidies in order to gain political popularity (Morris, Kelly, Kopicki & Byerlee, 2007). The primary role of subsidies, as noted by Ellis (1992, cited in Dorward, 2009), is to promote the adoption of new technologies and in turn increase agricultural productivity and production. This is achieved by allowing farmers access to purchased inputs (fertilizers and improved seed) at a lower cost, thereby creating an incentive for adoption that is mainly caused by farmers' cash constraints, low expectations and risk aversion of returns from investing in inputs. Subsidies, if coupled with other appropriate complementary policies, can furthermore be used to encourage the economically and technically efficient use of inputs by farmers, in addition to raising farm incomes. Tiba (2009) also noted that subsidies generate an interrelated impact on production, the price of inputs and staple crops, rural incomes, the development of markets, as well as growth and social development (enhancing the welfare of the poor).

Some of the pitfalls of subsidies, as noted in the literature, include distortion of the market (may crowd out and inhibit private sector investment in input markets), leakage to better-off farmers, and artificially low prices (may lead to the overuse of inputs or the adoption of input-intensive technologies, especially in developing countries, instead of more economically efficient labour-intensive production methods) (Dorward, 2009; Tiba, 2009).

The Zambian government subsidy programme, initially known as the Fertilizer Support Programme (FSP) and currently as the Farmer Input Support Programme (FISP), is intended to help cushion and shield smallholder farmers against the adverse impact of economic reforms and the effects of unfavourable weather conditions that can destroy their asset base, thus curbing and mitigating the high poverty rates amongst these farmers (Seshamani, 2002).

Since its inception, FISP has undoubtedly improved small-scale farmers' access to agricultural inputs (i.e. fertilizers and improved maize seeds), distributing a total of 422 000 metric tons of fertilizer covering a total of 1 505 000 hectares of small-scale maize. Annually, the programme supplies an average of 60 000 metric tons of fertilizer covering about 150 000 smallholder farmers countrywide (MACO, 2009).

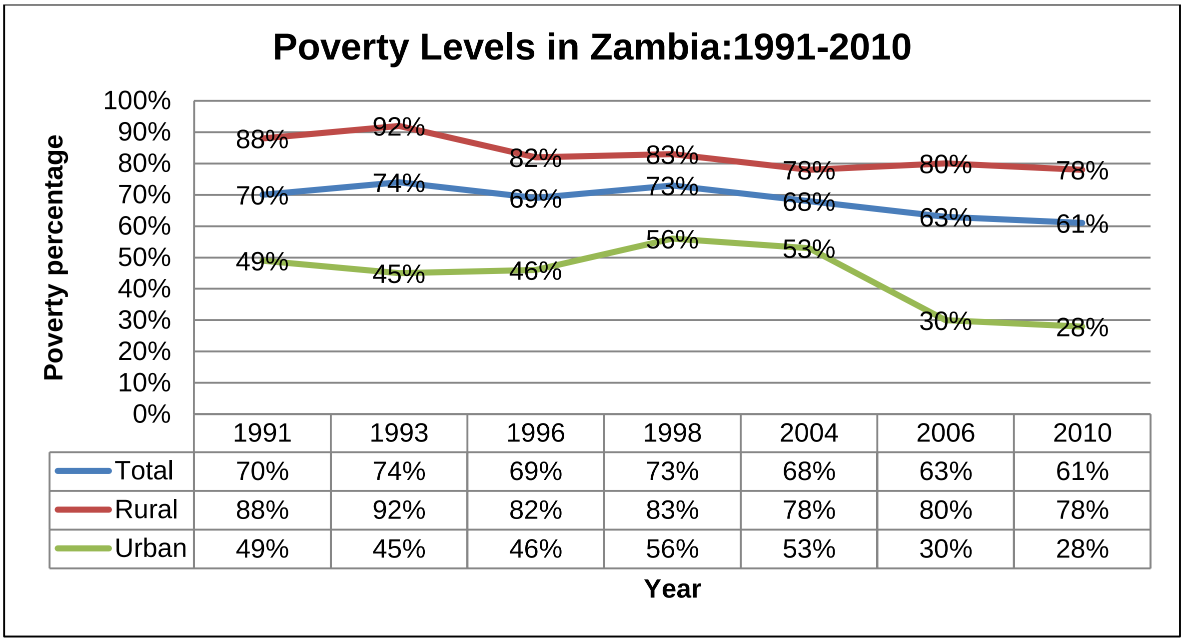
It is rather ironic that the government has spent over 20 % of the nation's GDP in supporting maize production and subsidising inputs for farmers, yet only maize production has increased and rural poverty remains high (Jayne, Mason, Burke, Shipekesa, Chapoto & Kabaghe, 2011). This has been attributed to the prescribed FISP participation requirements, especially in terms of land and explicit targeting, which tend to exclude poor rural households. CSO survey data further reveals that FISP fertilizer and maize seed have been allocated to households with greater capital assets and large farms (Burke, Jayne & Sitko, 2012). In Zambia, FISP is a key poverty reduction strategy, but has systematically been targeting the rich within the small- and medium-scale farming sectors, which suggests that poverty reduction stands at a lower priority level than the goal of increasing national maize surplus production.

2.3 POVERTY IN ZAMBIA

Tembo and Sitko (2013), using CSO figures, found that although Zambia's poverty rate has declined over time, it remains high, particularly in rural areas. Despite strong economic growth over the past decade, there has been very little progress in terms of reducing poverty, with 78 % of Zambia's rural population living in poverty in 2010 (Tembo & Sitko, 2013).

As seen in **Figure 2**, the total poverty level, estimated at 70 % in 1991, has remained high, reaching its peak in 1993 at 74 % and declining to its lowest level in 2010. Rural poverty increased from 78 % in 2004 to 80 % in 2006 before dropping to 78 % in 2010. In urban areas, the decline in poverty was more pronounced, exemplified by phenomenal growth in the proportion of non-poor people from 51 % to 72 % between 1991 and 2010, compared to an increase from 12 % to 22 % in rural areas over the same period. Contributing to these trends were the effects of policies for trade liberalisation, foreign investment and the sale of government housing, amongst others, which mostly favoured urban areas.

Jorgensen and Loudjeva (2005) identified the main determinants of poverty in Zambia as physical isolation and low levels of physical and social assets, human capital and land.



	1991	1993	1996	1998	2004	2006	2010
Total	70%	74%	69%	73%	68%	63%	61%
Rural	88%	92%	82%	83%	78%	80%	78%
Urban	49%	45%	46%	56%	53%	30%	28%

Figure 2: Percentage of Zambia's population living below the poverty line.

Source: Tembo and Sitko (2013)

2.3.1 Poverty surveys in Zambia

In 1991 the Zambian government, through the Central Statistical Office (CSO), began collecting poverty data based on household income, consumption and other living condition indicators in order to monitor living standards. Such surveys were prompted by the structural adjustment programmes being undertaken in the country, hence the need to monitor the social dimensions of these programmes and to analyse the effect of such activities on different segments of the country's population. This was initiated by the first Priority Survey (PS I), followed by PS II in 1993, and then by broader surveys such as the Living Conditions Monitoring Surveys (LCMSs). To date, a total of eight indicator monitoring surveys have been conducted (Chibuye, 2011; Lekprichakul, 2010).

2.4 DESCRIPTION OF THE STUDY AREA

The study was conducted in the major maize-growing provinces of Zambia, situated in either agro-ecological zone II or III, thus providing the study areas of interest. The study focused on all FISP beneficiary and non-beneficiary maize-producing smallholder farmers for the 2010/2011 agricultural growing season.

2.5 DESCRIPTION AND LOCATION OF THE STUDY

Zambia is divided into three major agro-ecological zones, namely zones I, II and III, mainly based on the annual rainfall **(Figure 3)**. Zone I (AEZ I) is located in the southern parts of the Southern and Western provinces, including the Zambezi and Luangwa valleys, and is characterised by low altitude that in turn brings about high temperatures, low erratic rainfall (less than 800 mm per annum), a short growing season (80 to 129 days), and a propensity for drought. With its sandy soils and poor fertility making it generally not viable for arable agriculture, it is one of Zambia's poorest regions. In this zone, maize is mostly grown when provided under the subsidised programme.

Zone II (AEZ II) covers the central parts of the country, including the Lusaka, Eastern and Southern provinces. It is characterised by good soils and higher rainfall (800 to 1 000 mm) than AEZ I, therefore supporting a range of crops in addition to the staple crop of maize. This region also receives significant support and assistance from both the government and the private sector, as it is Zambia's ideal agricultural zone and is highly populated.

Zone III (AEZ III) comprises large areas of the North-Western, Copperbelt, Luapula and Northern provinces and contains many of the country's major rivers and lakes. The soils tend to be sandy and acidic, with significant leaching due to high rainfall (above 1 000 mm). This region is also characterised by a low propensity for drought, a long growing season (120 to 150 days) and low temperatures during the growing season (Aregheore, 2009; MACO, 2009; Siegel, 2008).

The study was based on the six provinces lying within the two major agro-ecological zones, namely AEZ II and AEZ III. The Central, Eastern, Lusaka and Southern provinces are situated in AEZ II, while the Copperbelt and Northern provinces are situated in AEZ III. These provinces lie in the maize belt of Zambia where the bulk of the population is concentrated, thus representing the majority of the subsidy-targeted population. The study focused on all FISP beneficiary and non-beneficiary maize-producing smallholder farmers for the 2010/2011 agricultural growing season.

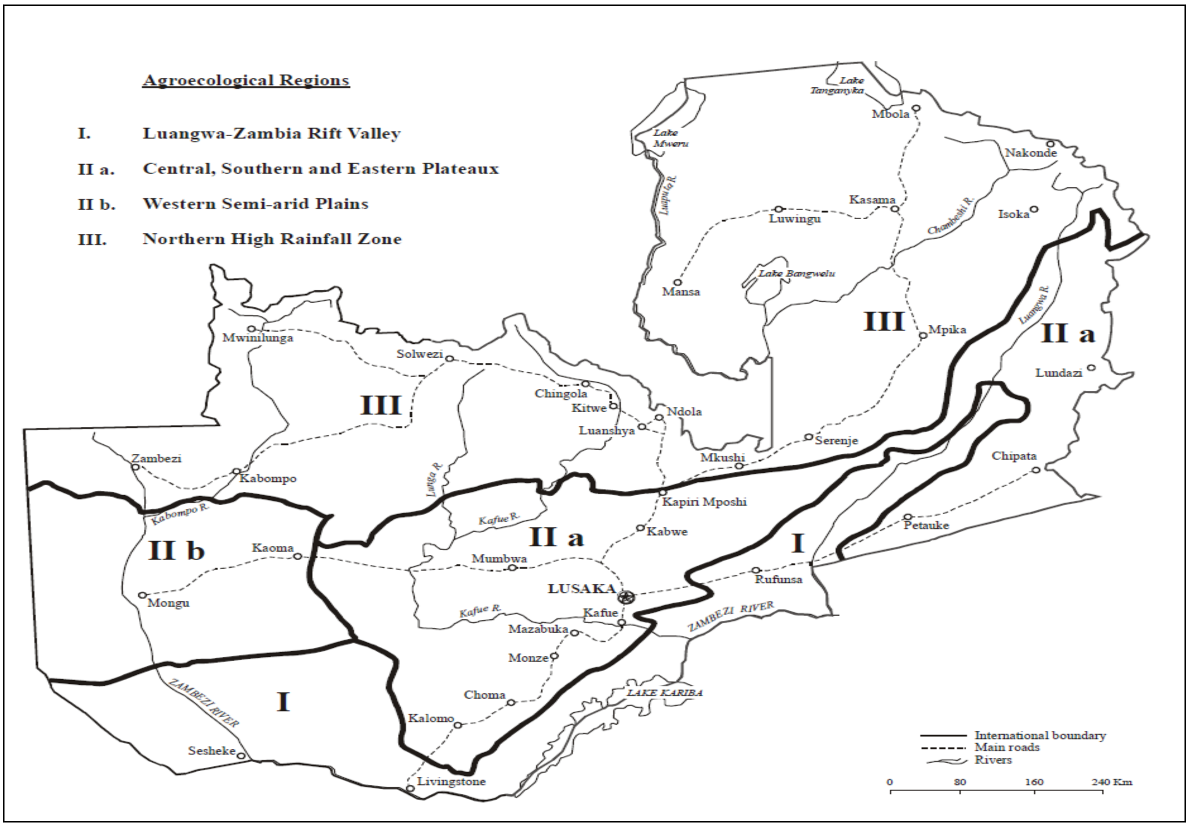


Figure 3: Agro-ecological zones of Zambia
Source: Siegel (2008)

CHAPTER 3

LITERATURE REVIEW

3.1 INTRODUCTION

This chapter reviews the general impact assessment theory, documenting selected findings of subsidy-related studies, before culminating in a conclusion.

3.2 THEORETICAL APPROACHES TO IMPACT ASSESSMENT

Governments, institutions and other practitioners, mainly in developing countries, are keen to determine the effectiveness of interventions designed to enhance certain sectors of their economy, such as poverty reduction or employment creation. In order to know the importance and benefits of a particular intervention, there is a need to investigate that intervention's expected results (as well as unexpected results). These policy quests are often possible only through impact evaluation, which explores the changes brought about by an intervention, and this must be based on hard evidence from survey data or related empirical approaches.

Although literature has shown that practitioners have not agreed on a universal definition of impact, there is some form of similarity in the various definitions thus far provided. For instance, the Development Assistant Committee (DAC) of the Organisation for Economic Cooperation and Development (OECD) defines impact as the "positive and negative, primary and secondary long-term effects produced by a development intervention, directly or indirectly, intended or unintended". This definition includes several important elements that need to be addressed by any impact evaluation, from cause and effect to negative and unanticipated consequences of an intervention. The other group of definitions focuses on specifically comparing the differences between what actually happened and what would have happened without the intervention, through the specification of some form of "counterfactual". The International Initiative for Impact Evaluation (3ie) defines impact in its Impact Evaluation Glossary as: "How an intervention alters the state of the world and impact evaluations typically focus on the effect of the intervention on the outcome for the beneficiary population". The similarity of the 3ie and DAC definitions of impact lies in the inclusion of the element of attribution, which is considered to be highly relevant to impact evaluation. Attribution is the extent to which the observed change in outcome is the result of the intervention, having allowed for all other factors that may also affect the outcome(s) of interest.

3ie therefore defines impact evaluation as "a study of the attribution of changes in the outcome to the intervention", while the World Bank (Khandker, Koolwal & Samad, 2010) defines impact evaluation as "an effort to understand whether the changes in well-being are indeed due to a project or programme intervention", and specifically that impact evaluation tries to determine whether it is possible to identify the programme's effect and to what extent the measured effect can be attributed to the programme and not to some other causes.

Besides the issues surrounding the impact evaluation definition, the methods or approaches used to evaluate impact is also at the centre of discussion. These are known as either quantitative or qualitative impact assessment approaches, with the major debate being that only quantitative approaches provide the "best" impact results. However, the main issues should rather centre on tracing the cause and effect of the intervention. Khandker *et al.* (2010) asserted that qualitative information is essential to a sound quantitative assessment; therefore the two approaches to impact evaluation are not mutually exclusive, but overlap at certain points. For example, many researchers have estimated the impact of government interventions that help uplift the welfare of the poor in both the developed and the developing world using quantitative methods of comparing adopters to non-adopters, smallholder farmers to commercial farmers, those who pay at subsidised prices to those who pay at commercial prices, and so forth. However, the impact of interventions such as subsidies may differ from continent to continent and from country to country when evaluated, due to qualitative factors such as cultural practices that are now becoming dynamic, climate change, soil type, crops grown and farm structure. But again, qualitative assessment on its own cannot assess impact. A mixture of qualitative and quantitative methods as an approach might therefore be useful in gaining a comprehensive view of the intervention's effectiveness.

The other challenge of evaluating the impact of interventions such as subsidies, as observed by Ricker-Gilbert, Jayne and Shively (2013), is that of the definition of programme participation can be modelled and defined in several ways. Participation (treatment) is characterised mainly by the way in which the subsidy programme is operationalized; therefore, for a researcher to clearly estimate the impact of a particular subsidy programme, there is a need to define what constitutes programme participation. In this study, programme participation is defined in terms of a binary indicator of whether or not the beneficiaries received maize seed and/or fertilizers in the 2010/2011 farming season.

3.3 IMPACT EVALUATION METHODS

Policy interventions like subsidy programmes can be evaluated according to several criteria. The basic question is whether the intervention has achieved the initial objectives, and to what extent. Evaluations should therefore focus on four areas **(Table 2)**, namely the impact on policy intervention characteristics, economic development, production, and input market. Various indicators can be calculated for each aspect, and the more indicators used in evaluations, the more comprehensive the picture of the efficiency of the input subsidy programme (Tiba, 2009).

Table 2: Evaluation indicators

Impact on	**Criteria**
Intervention characteristics	Cost-benefit analysis
	Monitoring of performance
	Timing
Economic impact	Changes in prices of inputs
	Changes in prices of outputs
	Impact on labour market
	Impact on growth and consumer /producer welfare
Production	Replenishing soil fertility
	Increase in production
	Increase in productivity
Input market	Leakage of subsidy
	Increase in input use
	Displacement of commercial sales impact on markets

Source: Tiba (2009)

This is not enough, however, because a researcher still needs to overcome what is known as the evaluation problem. Therefore, to know the effect of a policy intervention on participating individuals, there is a need to compare the observed outcome (factual) with the outcome that would have resulted had that person not participated in the intervention (counterfactual). In reality, only one outcome – the factual outcome – is observed, while the counterfactual outcome cannot be observed, and this could be an outcome that would result had the participating individual not participated or had the non-participating individual participated in the intervention – hence the evaluation problem. In this regard, programme evaluations tend to be difficult due to missing data. All evaluation approaches therefore try to provide an estimate of the counterfactual and use it to identify the programme intervention effect (Bryson, Dorsett & Purdon, 2002; Khandker *et al.*, 2010).

The counterfactual problem can be overcome in two ways: firstly by using the 'with and without' comparison and secondly by using 'before and after' comparisons. In the former approach, the researcher will compare what would have happened to the outcome of the programme intervention had the programme not existed, therefore a proper comparison group that is a close counterfactual of the programme is required. In the latter approach, it could be a comparison between pre-programme and post-programme outcomes of participants, but such a method would not give an accurate assessment because many other factors (outside the programme) may have changed over the period and need to be accounted for.

3.4 EXPERIMENTAL VERSUS NON-EXPERIMENTAL DESIGNS

Experimental evaluations operate by creating a control group of individuals who are randomly denied access to an intervention. A random assignment creates a control group comprising individuals with identical distributions of observable and unobservable characteristics to those in the treatment group (within sampling variation). This overcomes the selection problem, as participation is randomly determined. Practically, however, experiment designs are rarely used due to several concerns: Experiment designs, besides the likelihood of creating bias estimates through the randomisation bias (the experiment itself altering the framework within which the intervention operates) are often costly and require close monitoring to ensure that they are effectively administered. They may also require informing potential participants of the possibility of being denied treatment, and the potential for denying treatment can pose ethical questions that are politically sensitive. These concerns may reduce the chances of an experiment being considered as a means of evaluating an intervention (Bryson *et al.*, 2002).

Although experimental evaluation designs have the aforementioned drawbacks, in theory they are considered by far the most robust means of estimating programme intervention effects (Bryson *et al.*, 2002; Khandker *et al.*, 2010). However, in the literature, or rather in practice, many programme evaluations use non-experimental techniques that mimic or try to have an observational analogue of a randomised experiment (Khandker *et al.*, 2010). The use of these non-experimental techniques is mostly based on the characteristics of the intervention and the nature and quality of the available data. These non-experimental techniques all use what are known as identifying assumptions so as to identify the causal effect of a programme on the outcome of interest, but the fewer the assumptions the better the technique in estimating the programme effects (Bryson *et al.*, 2002).

With matching non-experimental techniques, a researcher attempts to develop a counterfactual that is as similar to the treatment group as possible in terms of observed characteristics, on the premise that from a group of non-participants, there will be individuals who are observationally similar to participants in terms of characteristics not affected by the programme. Participants are thus matched with observationally similar non-participants, and then the average difference in outcomes across the two groups is compared to achieve the programme treatment effect. If one assumes that differences in participation are based solely on differences in observed characteristics, and if enough non-participants are available to match with participants, the corresponding treatment effect can be measured even if treatment is not random (Caliendo & Kopeinig, 2008; Khandker *et al.*, 2010).

As pointed out by Khandker *et al.* (2010), the problem is to credibly identify groups that look alike, because even if households are matched along a vector X of different characteristics, one would rarely find two households that are exactly similar to each other in terms of several characteristics. Because many possible characteristics exist, a common way of matching households is through propensity score matching (PSM), whereby each participant is matched to a non-participant on the basis of a single propensity score, reflecting the probability of participating conditional on their different observed characteristics X (Rosenbaum & Rubin, 1983). PSM therefore avoids the "curse of dimensionality" associated with an attempt to match participants and non-participants on every possible characteristic when X is very large.

3.5 PRO-POOR PROGRAMMES

The increasing number of poor people in the world, especially in developing countries, has brought about policies targeting the poor. In the developmental literature, the term that is widely used for these policies is 'pro-poor'. Curran and Renzio (2006) and the World Bank (2000) define the poor as those who lack command over basic consumption needs, including food and non-food components.

In the literature the definition of 'pro-poor' is extremely vague and this has become quite challenging to the researchers and policymakers working on poverty issues. There are so many definitions that have been provided in the literature, but this study concentrates on two approaches used by Curran and Renzio (2006), namely the absolute and relative approaches.

The *absolute* approach looks exclusively at the direct benefit of a policy measure on the poor population. The benchmarks and indicators for such a measurement are not prescribed, but assume that a 'poverty line' has been specified to differentiate between those below the line (the poor) and those above the line (the non-poor). Pro-poor policies are therefore defined as those that allow for the maximum number of people to cross above the poverty line, regardless of what happens to the non-poor.

The *relative* approach determines the pro-poorness of a policy measure by looking at how much the welfare of the poor improves in relation to the non-poor – or more specifically, how much a policy measure *disproportionately* benefits the poor in comparison with the non-poor. As a consequence, a policy is seen as being 'pro-poor' if its positive impacts are greater for the poor than for the non-poor.

The previous paragraphs focused on the term pro-poor and it is defined by different approaches, but what does it entail for a programme to be denoted pro-poor? Kakwani and Son (2006) defined a government programme as pro-poor "if it provides greater benefits to the poor compared to the non-poor", while Van Domelen (2007) defined a programme as pro-poor "if the incidence of the programme beneficiaries or resources going to the poor is more than their relative share in a given population or simply programmes in which the poor are overrepresented".

Following the World Bank (2000) and Van Domelen (2007), for purposes of this research, a pro-poor programme or intervention is defined as a programme that specifically directs efforts, resources and/or benefits to improving the wellbeing of the poor majority of its population. The World Bank and Van Domelen definitions are used in this study, as they seem to be robust and straight to the point, viewing poverty largely in monetary terms and thus giving a dimension of poverty that can be directly measured. The latter views are also a generally more precise reflection of a household's ability to satisfy their much-needed basic needs.

3.6 IMPACT ASSESSMENT-RELATED STUDIES

Several researchers around the world have conducted studies on public spending, poverty, welfare indicators and the evaluation techniques of such programmes. The following section provides the findings of a few selected studies related to the one at hand. The first part discusses studies based on the welfare impact and the effect of poverty linkages with agricultural production, while the second part looks at studies that evaluate the impact of public spending and/or agriculture subsidies in relation to the intended beneficiaries.

3.6.1 Studies based on welfare and the effect of poverty linkages with agricultural production

Perova and Vakis (2009), in their analysis of the quantitative welfare impact of a conditional cash transfer programme in Peru, using non-experimental evaluation techniques, concluded that within two years of implementation, the programme had managed to improve key welfare indicators of the programme recipients. Therefore the programme had had a moderate impact in terms of reducing poverty and increasing monetary measures of both income and consumption. Likewise, in a study exploring how farm productivity affects poverty in Tanzania, Sarris, Savastano and Christiaensen (2006) found that poorer households did not only possess fewer assets, but were also much less productive. They therefore concluded that agricultural productivity directly affects household consumption and hence overall poverty and welfare.

3.6.2 Studies based on types of public spending with the greatest impact on poverty reduction

Fan, Hazell and Thorat (2000) analysed the trend of different sources of poverty reduction over the past four decades starting in the 1960s. They found that most government spending and subsidies contributed most to reducing rural poverty over three decades, while fertilizer subsidies, investment in roads and credit subsidies had the greatest poverty-reducing impact in the 1960s and 1970s. Education, roads and irrigation investment had a relatively greater poverty-reducing impact than any other type of government spending in the 1980s, and lastly the impact of education and road spending on poverty reduction remained very strong in the 1990s.

3.6.3 Studies based on the impact evaluation of subsidy programmes

Many researchers have attempted to measure the impact of subsidies on different livelihood outcomes. In Africa there have been several studies on Malawian agricultural subsides, attracting a number of renowned researchers whose studies are discussed below.

Ricker-Gilbert *et al.* (2009) evaluated the impact of the Malawian fertilizer subsidy programme on the yields of participants compared to those who obtained fertilizer at commercial prices. Using panel data, descriptive results indicated that maize plots using commercial fertilizer obtained higher yields per kilogram of fertilizer than maize plots using subsidised fertilizer. Conversely, the results obtained using a fixed-effects estimator indicated that when other factors were controlled for, maize plots using subsidised fertilizer obtained a higher yield response than other plots. They concluded that the results seemed to be influenced by a group of farmers who had used no fertilizer before the subsidy programme began, but started using subsidised fertilizer after the programme was implemented. This group of farmers obtained significantly higher yields in the year when they received the subsidy than did the remaining farmers in the sample during that year. The policy implication of this study is that for the subsidy programme to be effective, government should specifically target fertilizer subsidies to farmers who lack access to commercial markets.

A similar study was conducted by Chirwa (2010) who used two datasets from different production periods to compare the impact of targeted fertilizer input subsides on food expenditure. Using treatment effects, the results indicated that the subsidy programme implemented in Malawi prior to 2004/2005, which focused on one tenth of a hectare, had a significant negative impact on household food expenditure compared to the refined programme implemented in 2006/2007, which targeted about half a hectare for marginalised smallholder farmers.

Chibwana *et al.* (2011) also evaluated the impact of agricultural inputs on cropland allocation in Malawi. Using a two-step regression strategy to control for endogenous selection into the programme, they found a positive correlation between participation in the programme and the amount of land planted with maize and tobacco. The results also suggested that participating households simplified crop production by allocating less land to other crops (e.g. groundnuts, soybeans and dry beans). The policy implications of the findings were thus aimed at promoting both food self-sufficiency and crop diversification in low-income settings.

3.7 CONCLUSION

The literature that was reviewed provided specific insight and was thus used to guide the study in evaluating the impact of FISP in Zambia.

CHAPTER 4

EVALUATION METHODS AND THEIR APPLICATION

4.1 INTRODUCTION

This chapter reviews the most common evaluation methods and the strengths and weaknesses of each. The conceptual framework to explain the theory of change for a subsidy programme is also discussed.

4.2 PROPENSITY SCORE MATCHING (PSM)

The PSM approach attempts to capture the effects of different observed covariates X on participation in a single propensity score or index. The outcomes of participating and non-participating households with similar propensity scores are then compared to obtain the programme effect. Households for which no match is found are dropped, because no basis exists for comparison. PSM constructs a statistical comparison group that is based on a model of the probability of participating in the treatment T conditional on observed characteristics X, or the propensity score: $P(X_i) = \Pr(T_i = 1 \mathrm{I} X_i)$ and the estimation of the counterfactual is $E[Y_i \mathrm{I} T_i = 1, P(X_i)] = E[Y_i \mathrm{I} T_i = 0, P(X_i)]$. The basic principal of this approach lies in the estimation of propensity scores, and common practice uses predicted probabilities of being in the treatment group or in the non-treatment group derived from dichotomous logit or probit models, including covariates X. Therefore, based on certain assumptions, matching on $P(X_i)$ is as good as matching on X_i. The necessary assumptions for identification of the programme effect are (a) conditional independence and (b) presence of a common support (Bryson *et al.*, 2002; Caliendo & Kopeinig, 2008; Gretha, 2011; Khandker *et al.*, 2010; Rosenbaum & Rubin, 1983).

4.2.1 Assumption of conditional independence (CIA)

Conditional independence (unconfoundness assumption) states that given a set of observable covariates X that are not affected by treatment, potential outcomes Y are independent of treatment assignment T. If Y_iT represent outcomes for participants and Y_iC outcomes for non-participants, conditional independence, which is also equivalent to the absence of selection bias based on unobservable heterogeneity, can be expressed as:

$$(Y_i^T Y_i^C) \perp T_i | X_i \tag{4.1}$$

CIA is a strong assumption and is not a directly testable criterion; it depends on specific features of the programme itself. For instance, if unobserved characteristics determine programme participation, CIA will be violated and PSM is not an appropriate method. Therefore, having a rich set of pre-programme data or theoretical or empirical evidence on the nature of selection into a programme will help support CIA by allowing the evaluator to control for as many observed characteristics as might be affecting programme participation (Gretha, 2011; Khandker *et al.*, 2010).

4.2.2 Assumption of common support

A second assumption is the common support (overlap condition) implied by $0 < P(T_i = 1|X_i) < 1$. As explained by Heckman, LaLonde and Smith (1999) and also outlined in Khandker *et al.* (2010), this condition ensures that treatment observations have comparison observations "nearby" in the propensity score distribution. They specifically stress that the effectiveness of PSM also depends on *having a large and roughly equal number of participant and nonparticipant observations* so that a substantial region of common support can be found. For estimating the average treatment on the treated (ATT), this assumption can be relaxed to $P(T_i = 1|X_i) < 1$.

Treatment units will therefore have to be similar to non-treatment units in terms of observed characteristics *unaffected* by participation; thus, some non-treatment units may have to be dropped to ensure comparability. However, sometimes a non-random subset of the treatment sample may have to be dropped if similar comparison units do not exist (Bryson *et al.*, 2002; Ravallion, 2007). This situation is more problematic, because it creates a possible sampling bias in the treatment effect. Examining the characteristics of dropped units may be useful in interpreting potential bias in the estimated treatment effects. Deleting or dropping all observations with a propensity score smaller than the minimum and larger than the maximum in the opposite group considered to have weak common support is thus encouraged, as it is only in the area of common support that inferences can be made about causality (Caliendo & Kopeinig, 2008; Khandker *et al.*, 2010).

4.2.3 Advantages and disadvantages of PSM relative to other evaluation techniques

The following section provides some of the advantages of PSM relative to other non-experimental evaluation techniques, as outlined in Bryson *et al.* (2002).

With regard to the two assumptions outlined above, PSM has two clear disadvantages relative to experimental techniques. The first concerns meeting CIA. In the case of random assignment, properly conducted, the likelihood that the treated and non-treated populations are similar on both observable and unobservable characteristics is almost certain. This is not true in the case of PSM, which takes into account the selection on observables only. Secondly, whereas PSM can only estimate treatment effects where there is support for the treated individuals among the non-treated population, random assignment ensures that there is common support across the whole sample. These considerations make experimental techniques unambiguously superior to PSM. However, practical considerations are also important in the design and execution of programme evaluations, and in some circumstances these practical considerations may favour PSM over random assignment.

Although PSM has the aforementioned weaknesses when compared to experimental techniques, generally matching is unambiguously preferred to standard regression methods for two reasons. Firstly, matching estimators highlight the problem of common support, since treatment effects can only be estimated within the common support. Where there is poor overlap in support between the treated and the non-treated, this raises questions about the robustness of traditional methods relying on functional form to extrapolate outside the common support. Secondly, matching does not require functional form assumptions for the outcome equation (that is, it is non-parametric). Regression methods impose a form on relationships, which may or may not be accurate and which PSM avoids: this is valuable since these functional form restrictions are usually justified neither by economic theory nor the data used.

Whether matching is advantageous relative to methods that deal with selection on the unobservable (like the instrumental variable regression) depends on the available data and the institutional nature of the selection process into the treatment. Matching is only feasible where there is a firm understanding, based on theory and past empirical evidence, of the determinants of programme participation and the outcomes of interest. If this information is available, and the data is available to make CIA plausible, then matching is feasible. This avoids the search for a good instrument by which to identify the selection process, and separates this process from the one governing outcomes. The appropriateness of the exclusion restriction identifying the two equations required for the instrumental variable (IV) approach is an untestable assumption, and one that is often inherently difficult to make. This is because it is often difficult to find variables affecting the probability of programme participation that do not affect the outcomes other than through their effect on participation. However, if such instruments are available, the IV and method is feasible. If there are no good instruments available and CIA is not plausible, but longitudinal outcome data is available and selection is plausibly on the fixed component of the unobservables, the analyst can use the difference-in-difference estimator, perhaps in combination with matching.

Furthermore, with matching, there is no need for the assumption of constant additive treatment effects across individuals, which is required in simple regression and the Heckman and bivariate normal selection estimation procedures. Instead, heterogeneous treatment effects are permitted and can be retrieved via subgroup analysis, which involves selecting the subgroup of interest and re-matching within that group. This makes PSM a flexible tool for studying programme effects on groups of particular interest.

4.3 MATCHING ESTIMATORS

When evaluating the effect of an intervention, once the propensity scores are estimated the interest of the evaluator shifts to estimation of average treatment effects. This requires a matching estimator to be selected so as to describe how the comparison units relate to treated units. Different matching algorithms can be used to assign participants to non-participants on the basis of the propensity score. Doing so requires calculating a weight for each matched participant-to-non-participant set. Since different matching algorithms are assigned different weights, this also affects the resulting intervention estimate (Khandker, Bakht & Koolwal, 2006). In this study four matching algorithms that have received considerable attention in the literature are discussed (Error! Reference source not found.) and are mainly based on Bryson *et al.* (2002), Caliendo and Kopeinig (2008) and Khandker *et al.* (2010).

Table 3: Different matching algorithms

Matching Algorithm	Main Characteristic
Nearest Neighbour (NN)	▪ With/Without replacement
Calliper or Radius	▪ Max tolerance level imposed (calliper) ▪ 1=NN only or more (radius)
Stratification or Interval	▪ Number of strata/intervals
Kernel	▪ Kernel function (weighted sum of comparison units)

Source: Adopted from Caliendo and Kopeinig (2008)

I. *Nearest Neighbour (NN)*: This is one of the most straightforward and the most frequently used matching techniques in the literature. NN matching works in such a way that each treatment unit is matched to the comparison unit with the closest propensity score, and several variants are proposed. NN 'with replacement' creates the possibility of matching a given untreated unit to more than one treated as a match, whereas NN 'without replacement' considers using the untreated units only once. The former involves a trade-off between bias and variance – that is, if we allow replacement, the average quality of matching will increase and the bias will decrease. When using the latter technique, it is suggested that the evaluator ensures that ordering is randomly done otherwise a problem may arise as estimates obtained in NN matching without replacement depend on the order in which observations are matched.

II. *Calliper or Radius Matching*: This is one technique that overcomes the problem of a high difference between a treated unit and its closest untreated unit neighbour as when using NN matching. This problem results in poor matches, but by imposing a threshold or tolerance on the maximum propensity score distance (calliper) this can be avoided. It thus uses the mean of all untreated units within the calliper. Imposing a calliper works in the same direction as allowing for replacement. A higher number of dropped untreated units is, however, likely to potentially increase the chance of sampling bias. A benefit of the calliper approach is that it uses only as many comparison units as are available within the calliper and therefore allows for usage of extra (fewer) units when good matches are (not) available, whereas its possible drawback is that it is difficult to know a priori what choice for the tolerance level is reasonable.

III. *Stratification or Interval Matching*: This is implemented by partitioning the common support into different strata (or intervals), and calculates the intervention's impact within each interval. Specifically, within each interval, the intervention effect is the mean difference in outcomes between treated and untreated units. A weighted average of these interval impact estimates yields the overall intervention impact, taking the share of participants in each interval as the weights.

IV. *Kernel Matching*: One risk with the methods described above is that only a small subset of untreated units will ultimately satisfy the criteria to fall within the common support and thus construct the counterfactual outcome. Non-parametric matching estimators, such as the kernel approach, match each treated unit to a weighted sum of comparison units, with the greatest weight assigned to units with closer scores. This approach has the advantage of having a lower variance because more information is used, whereas its drawback is associated with the likelihood of it using units that are bad matches. Therefore, proper imposition of the common support condition is suggested when using kernel matching.

With the choice of the four matching algorithms in the hands of the evaluator, it is thus important to note the conclusion of Bryson *et al.* (2002), namely that in theory, all approaches should yield the same results when applied to large datasets. However, this leaves the question of what constitutes a large dataset. It is reassuring that in practice, the choice of matching method often appears to make little difference, and in small samples the choice of matching approach can be important. However, there appears to be little formal guidance in the choice of optimal method, and choice should thus be guided in part by the distribution of scores in the comparison and treatment samples.

4.4 SENSITIVITY ANALYSIS – ROSENBAUM BOUNDS (RBOUNDS)

As alluded to in the PSM discussion, the estimation of treatment effects with matching estimators is based on CIA – that is, selection in a programme is based on observable characteristics. Checking the sensitivity of the estimated results with respect to deviations from this identifying assumption has become an increasingly important topic in impact evaluation studies (Becker & Caliendo, 2007), because if there are unobserved variables that affect assignment into treatment and the outcome variable simultaneously, a 'hidden bias' might arise. It should thus be clear that matching estimators are not robust against this 'hidden bias' (Caliendo & Kopeinig, 2008). Since it is a well-known fact that governments do not randomly distribute subsidies, especially input subsidies, to farmers, and it is also not possible to estimate the magnitude of selection bias with non-experimental data, this problem is eased with the bounding approach proposed by Rosenbaum (2002). This Rbounds approach therefore determines how strongly an unobserved variable must influence the selection process in order to undermine the implications of matching analysis. In other words, the purpose of the Rbounds procedure is to determine if the average treatment effect may be modified by unobserved variables, thus creating a hidden bias.

Assuming that participation probability is given by $P(X_i) = P(T_i{=}1|X_i)$ =F $(\beta X_i{+}\gamma\mu_i)$, where X_i are the observed characteristics for individual i, μ_i is the unobserved variable and γ is the effect of μ_i on the participation decision. Clearly, if the study is free of hidden bias, γ will be zero and the participation probability will solely be determined by X_i. However, if there is hidden bias, two individuals with the same observed covariates X have differing chances of receiving treatment. Assuming a matched pair of individuals i and j, and further assuming that F is the logistics distribution, the odds that individuals will receive treatment are then given by $\frac{P(X_i)}{1-P(X_i)}$ and $\frac{P(X_j)}{1-P(X_j)}$, where the odds ratio is given by:

$$\frac{\frac{P(X_i)}{1-P(X_i)}}{\frac{P(X_j)}{1-P(X_j)}} = \frac{P(X_i)(1-P(X_j))}{P(X_j)(1-P(X_i))} = \frac{\exp(\beta X_j+\gamma\mu_j)}{\exp(\beta X_i+\gamma\mu_i)} = \exp[\gamma(\mu_i+\mu_j)] \quad (4.2)$$

If both units have identical observed covariates, as implied by the matching procedure, the X-vector is cancelled out, but still both individuals differ in their odds of receiving treatment by a factor that involves the parameter γ and the difference in their unobserved covariates μ. So if there are either no differences in unobserved variables ($\mu_i = \mu_j$) or if unobserved variables have no influence on the probability of participating ($\gamma = 0$), the odds ratio is one, implying the absence of hidden or unobserved selection bias.

It is now the task of sensitivity analysis to evaluate how inference about the programme effect is altered by changing the values of γ and ($\mu_i - \mu_j$). Following Aakvik (2001), and assuming for the sake of simplicity that the unobserved covariate is a dummy variable with $\mu_i \in \{0, 1\}$, a good example is the case where motivation plays a role for the participation decision and the outcome variable, and a person is either motivated (μ = 1) or not (μ = 0). Rosenbaum (2002) showed that (4.2) implies the following bounds on the odds-ratio that either of the two matched individuals will receive treatment:

$$\frac{1}{e^{\gamma}} \leq \frac{P(X_i)(1-P(X_j)}{P(X_j)(1-P(X_i)} \leq e^{\gamma} \qquad (4.3)$$

Both matched individuals have the same probability of participating only if $e^{\gamma} = 1$. If $e^{\gamma} = 2$, then individuals who appear to be similar (in terms of X) could differ in their odds of receiving treatment by as much as a factor of 2. In this sense, e^{γ}γ is a measure of the degree of departure from a study that is free of hidden bias (Rosenbaum, 2002).

Finally, DiPrete and Gangl (2004) concluded that the Rbounds approach can often provide reasonable confidence that a causal relationship between a treatment and an outcome variable exists even in the presence of potentially confounding variables, and that the Rbounds approach and IV estimation are complementary approaches, not competing ones.

4.5 POVERTY MEASURES

Poverty measurements are critical for researchers, project designers and policymakers, as they help in understanding the factors determining the poverty situation and designing interventions best suited to issues of poverty eradication, thus allowing for the assessment of the effectiveness of pro-poor policies to determine whether the poverty situation is indeed changing. Various definitions for wellbeing exist, and likewise various measures could also be applied to numerous dimensions (indicators) of wellbeing such as consumption, income and asset ownership. The subsequent sections explore two such measures utilising some of the above-mentioned indicators.

4.5.1 Foster, Greer and Thorbecke (FGT) measures of poverty

In line with the World Bank common practice of defining the poor as those who lack command over basic consumption needs, including food and non-food components, the poverty line is obtained by specifying a consumption bundle considered adequate for basic consumption needs, then estimating the cost of these basic needs. The poverty line is therefore defined as the minimum expenditure required to fulfil basic needs, or the threshold consumption needed for a household to escape poverty. The poverty line has been seen to be somewhat arbitrary, because the line between the poor and non-poor can be hard to define. It is thus best to think of the poverty line as the consumption or income level that separates the poor from the rest of the population (Haughton & Khandker, 2009; World Bank, 2000).

On the other hand, the United Nations Development Programme (UNDP) advocates for a poverty measure that takes into account the multidimensional component of poverty, because human welfare is multidimensional. Therefore, to reflect the multidimensionality of poverty, the UNDP uses a measure known as the multidimensional poverty index (MPI), which takes into account health, education and living conditions. The major drawback to the MPI is its insensitivity to short-run variations to external shocks, thus it is only ideal for measuring poverty in long- or medium-term situations. It is for this reason that income- or consumption-based welfare measures are commonly used, as they are more sensitive short-run and medium-term poverty indicators (Lekprichakul, 2010).

The most commonly used poverty measure is the headcount index or the share of population whose income or consumption is below the poverty line. Other measures, like the depth and severity of poverty, can help to better illustrate the poverty contours of a region, district or country. These measures are said to satisfy the desirable fundamental properties of such measures, with the additional advantage of being additively decomposable (Foster, Greer & Thorbecke, 1984; Haughton & Khandker, 2009).

The poverty measures (headcount index, intensity of poverty and poverty severity or inequality of poverty) described in the previous paragraph can thus be summarised in the modified Foster *et al.* (1984) classic class of decomposable formula shown below:

$$P_\alpha = \frac{1}{N}\sum_{i=1}^{M}\left(\frac{Z-Y_i}{Z}\right)^{\alpha}, where\ \alpha \geq 0 \qquad (4.4)$$

The measure P_0 (incidence of poverty) is simply the headcount ratio, P_1 (intensity of poverty) is the poverty gap index and P_2 (inequality of poverty) is the poverty severity index, which is sensitive to the distribution of living standards among the poor. Where Y_i is the average real spending of the household member I, Z is the poverty line, N is the number of people in the sample population, M is the number of poor people, and α can be interpreted as a measure of inequality aversion or coefficient. A larger α gives greater emphasis to the poorest of the poor.

4.5.2 Principal component analysis (PCA) method of calculating household wealth indices

PCA is a mathematical technique for extracting from a set of variables (assets) those few orthogonal linear combinations of the variables that capture the common information most successfully. Intuitively the first principal component of a set of variables is the linear index of all the variables that captures the largest amount of information that is common to all of the variables.

For instance, given a set of *K* variables, *a**1*j* to *a***K j*, representing the ownership of *K* assets by each household *j*, the principal components will start by specifying each variable normalised by its mean and standard deviation. This can be illustrated by $\alpha_{1j} = (\alpha_{1j}^* - \alpha_1^*)/\delta_1^*$ where α_1^* is the mean of α_{1j}^* across households and δ_1^* is its standard deviation. These selected variables are therefore expressed as linear combinations of a set of underlying components for each household *j*:

$$\alpha_{1j} = v_{11}A_{1j} + v_{12}A_{2j} + \ldots + v_{1K}A_{Kj}$$

$$\forall_j = 1, \ldots, j \qquad (4.5)$$

$$\alpha_{K1j} = v_{K1}A_{1j} + v_{K2}A_{2j} + \ldots + v_{kK}A_{Kj}$$

Where the As are the components and the vs are the coefficients on each component for each variable (and do not vary across households). The solution to the problem is indeterminate, because only the left-hand side of each line is observed. To overcome this indeterminacy, PCA finds the linear combination of the variables with maximum variance, usually the first principal component $A_{1j,}$ and then a second linear combination of the variables, orthogonal to the first, with maximal remaining variance, and so on. Technically the procedure solves the equations $(\boldsymbol{R} - \lambda I)\boldsymbol{V}_n = 0$ for λ_n and $\boldsymbol{V}_n$, where $\boldsymbol{R}$ is the matrix of correlations between the scaled variables (the αs) and $\boldsymbol{V}_n$ is the vector of coefficients on the *n*th component for each variable. Solving the equation yields the eigenvalues (or characteristic roots) of $\boldsymbol{R}$, λ_n and their associated eigenvectors $\boldsymbol{V}_n$. The final set of estimates is produced by scaling the $\boldsymbol{V}_n$s so the sum of their squares sums to the total variance.

The "scoring factors" from the model are recovered by inverting the system implied by equation (4.5), yielding a set of estimates for each of the *K* principal components:

$$A_{1j} = f_{11}\alpha_{1j} + f_{12}\alpha_{2j} + \ldots + f_{1K}\alpha_{Kj}$$

$$\forall_j = 1, \ldots, j \qquad (4.6)$$

$$A_{K1j} = f_{K1}\alpha_{1j} + f_{K2}\alpha_{2j} + \ldots + f_{kK}\alpha_{Kj}$$

The first principal component, expressed in terms of the original (un-normalised) variables, is therefore an index for each household based on the expression:

$$A_{1j} = \frac{f_{11}\left(\alpha^*_{1j} - \alpha^*_1\right)}{\delta^*_1} + \ldots + \frac{f_{1K}\left(\alpha^*_{kj} - \alpha^*_k\right)}{\delta^*_k} \qquad (4.7)$$

The assigned weights are then used to construct an overall 'wealth index', applying the following formula:

$$W_j = \sum_{i=1}^{k}\left[b_i\left(\alpha_{ji} - x_i\right)\right]/\delta_i \quad (4.8)$$

Where W_j is a standardised wealth index for each household, b_i represents the weights (scores) assigned to the (*k*) variables on the first principal component, α_{ji} is the value of each household on each of the *k* variables, x_i is the mean of each of the *k* variables, and δ_i is the standard deviations.

A negative index ($-W_j$) means that, relative to the communities' measure of wealth, the household is poorly endowed and hence worse off, while a positive figure (W_j) signifies that the household is well off. A zero value, which is also the sample mean index, implies that the household is neither well off nor worse off (Langyintuo, 2008).

The desirability of using input subsidies not only to achieve economic growth targets but also welfare goals has recently been noted in debates. Subsidies bring about income transfers to farmers and this is expected to result in greater savings and investment in assets, contributing to longer-run growth. To date, most studies on subsidy evaluation have focused either on agricultural productivity, land use, household income, increased use of inputs such as fertilizer, or income poverty. No study has directly compared programme impacts using asset accumulation as an indicator. Doing so would likely enhance the robustness of programme impact estimates, as looking at the assets[5] of the poor brings about a deeper understanding of their transition out of poverty.

In this study, to connect asset accumulation to the subsidy programme, a wealth index was created using PCA. While standard poverty measures provide static backward-looking measures, the "asset-based approach" offers a forward-looking dynamic framework that identifies asset-building thresholds, and measures movements in and out of poverty (Moser, 2006).

[5] In this study, household assets include all livestock owned, productive assets, household assets, social assets and consumer durable assets, and asset accumulation means to increase the real value of all types of assets of the household over a specified reference period.

4.6 CONCEPTUAL FRAMEWORK

The next section highlights the modified conceptual framework that supports pro-poor public intervention policies in increasing beneficiaries' welfare. It also points out how poverty reduction is linked to agricultural production.

Rogers (2012) and the United Nations Evaluation Group (UNEG, 2013) advocated the basing of an impact evaluation on a theory or model that tries to explain how an intervention is expected to lead to intended or observed impacts. This could be called a programme theory or a theory of change (ToC). The theory of change, although commonly used in international development by renowned local and international organisations like the United Nations and other civil society organisations in their quest to evaluate their programmes intended to support development outcomes (Vogel, 2012), the ToC can also be modified and used to illustrate a series of assumptions and links underpinning the presumed causal relationships between subsidies, agricultural productivity, asset accumulation and poverty reduction. Otherwise, failing to pay particular attention to the collection and use of data based on theory of change might lead to unclear findings and thus inappropriate policy responses (White, 2009). It is only through the theory of change that a plausible and evidence-based explanation of interventions can be provided.

Public spending by and large affects rural poverty through many channels, either directly or indirectly, and its impact can be assessed at several levels beginning from the farmers' household level through the district and provincial levels to the sector and national levels. For instance, investment in rural education and agricultural research increases farmers' income directly thorough agricultural productivity, which in turn reduces rural poverty. Indirect impact comes from improved non-farm job opportunities and higher agricultural wages brought about by growth in agricultural productivity. The urban poor are often considered to be net buyers of food grains, and they therefore benefit indirectly from rural public spending through increased agricultural output that often leads to lower food prices (Benin, Pratt, Fan & Breisinger, 2008; Dorward, 2009).

Figure 4 below outlines the modified United States Agency for International Development (USAID) and Regional Strategic Analysis and Knowledge Support (ReSAKSS) conceptual framework for poverty reduction used in this study. It highlights the potential channels through which public spending on agriculture, specifically in rural areas, can affect agricultural production (food production), rural food, rural incomes and rural poverty.

As indicated in **Figure 4**, poverty is linked to agricultural production, which in turn is a function of income and its underlying determinants. These determinants can furthermore be linked directly to poverty as welfare indicators, with everything being influenced by the policy and social environments.

Similarly, in his conceptual framework for investigating the impact of agricultural impact subsidies, Dorward (2009) stressed the importance of looking at the effects of subsidies on rural households amongst both recipients and non-recipients in terms of crop purchases, input access and use, farm and non-farm activities, income, welfare and food security. Dorward (2009) further provided a number of potential outcomes of subsidy programmes, including incremental production, incremental input use, increased productivity, and welfare and growth impacts.

In the literature it is also hypothesised that agricultural productivity and food production are related to overall household income (expenditure) and consumption (Irz, Lin, Thirtle & Wiggins, 2001; Sarris *et al.*, 2006). Sarris *et al.* (2006) further observed a negative correlation between agricultural productivity and poverty, but with the net welfare effect being dependent on whether households are net food buyers or sellers. Other plausible links between poverty and agricultural production include that which brings about gains in welfare and rural human capital as increased food production and farming incomes allow for better nutrition amongst rural workers and greater investment in education and health (Irz *et al*., 2001).

Datt and Ravallion (1998, cited in Irz *et al.,* 2001) explained the pro-poor character of agricultural production by estimating a simultaneous equation model of poverty determination. The results showed that land yield is inversely related to a variety of poverty measures, with an elasticity ranging from one to two. Thorbecke and Jung (1996, cited in Irz *et al*., 2001) concluded that the bulk of poverty reduction is achieved by growth within agriculture, while Irz *et al.* (2001) accentuated the impact of increasing agricultural productivity on poverty reduction by concluding that a 10 % increase in crop yields leads to a reduction of between 6 % and 10 % in the number of people living on less than US$ 1 per day.

The Agriculture Policy Guide of the Chronic Poverty Advisory Network (2012) clearly demonstrates and explains the relationship between assets, productivity and poverty reduction, stating that the role of asset accumulation is crucial to understanding poverty dynamics and addressing the constraints that prevent poor rural farmer households from improving their productivity. Rural household are said to be poor mainly due to the low levels of assets they possess, as well as their limited returns on these assets, leading to an inability to accumulate further assets. In other words, the impact of asset ownership on household welfare depends mainly on households being able to use their assets as components of livelihood strategies.

Assets can be grouped into five types of capital: physical (productive assets, housing); natural (land, soil, atmosphere, forests, minerals, water and wetlands); human (knowledge, skills, health, nutrition); financial (cash, bank deposits, livestock, other stores of wealth); and social (networks and informal institutions that facilitate coordination and cooperation) (Chronic Poverty Advisory Network, 2012; Ford, 2004; Moser, 2006). Productive assets like livestock and farm equipment raise the poor's asset bases for eventual leverage, and livestock assets are frequently used as a means of insurance. Human assets like education normally give people the knowledge to improve their livelihoods and provide access to formal employment, with some studies having shown this to be an important escape route from poverty. Social capital assets can also have direct benefits in rural communities through economies of scale (farmers putting production together) or indirect benefits providing an enabling environment for technology transfer and lobbying. And lastly, infrastructure such as storage and processing facilities allows poor farmers to maximise returns from those assets they do hold. This generally shows that asset accumulation and increased productivity (income) can be mutually reinforcing while at the same time providing for subsistence.

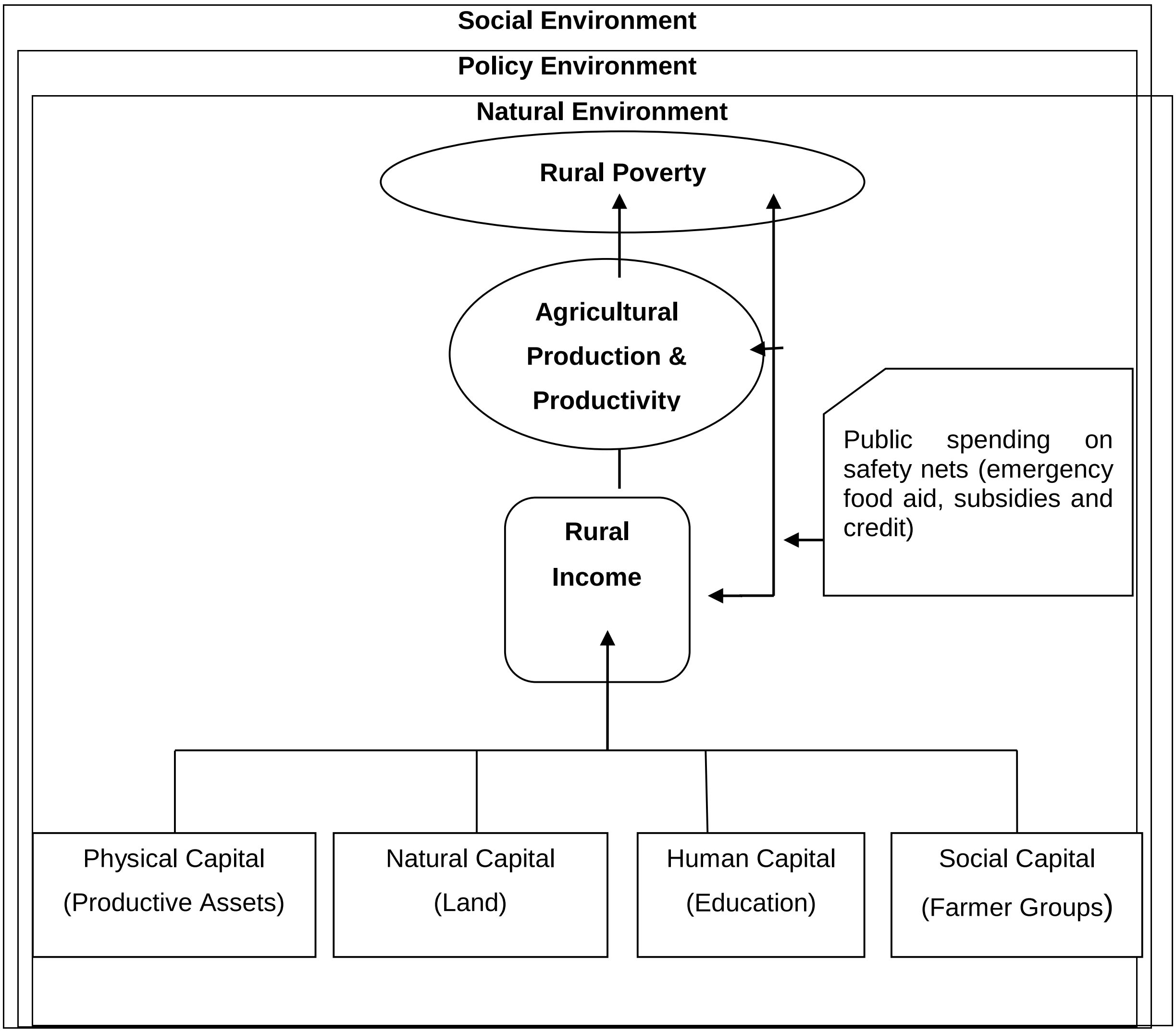


Figure 4: Poverty reduction conceptual framework
Source: Adapted from Benin *et al.* (2008) and Riely, Mock, Cogill, Bailey and Kenefick (1999)

4.7 CONCLUSION

The methods reviewed in this chapter formed the foundation for the study. The PSM approach was the core analysis tool, while both FGT and PCA were used to ascertain the poverty impact of policy and provide a general profile of the treated and untreated units.

CHAPTER 5

METHODOLOGY AND CHARACTERISTICS OF THE SAMPLED HOUSEHOLDS

5.1 INTRODUCTION

This chapter focuses on the inquiry strategy used in the study, as well as the sampling methods, data collection, data analysis, and general characteristics of the sampled households.

5.2 DESCRIPTION OF INQUIRY STRATEGY

For one to carry out an impact assessment of a public programme, there is a need to purposely design a strategy that will facilitate a relevant comparison between the treated and untreated in line with programme goals or objectives. The best impact evaluation procedure should therefore be able to precisely assess the mechanisms whereby beneficiaries are responding to the intervention (Khandker *et al.,* 2010). The most appropriate inquiry strategy for this study was determined to be an empirical survey utilising secondary data. A single cross-sectional survey dataset representing all the beneficiaries and non-beneficiaries of FISP in the study area for the 2010/2011 growing season was compiled, with the unit of observation being a single household. The principal variables collected were both interventional-influenced variables (household-level FISP impact indicators, for example household maize production) and non-interventional-influenced variables (indicators not influenced by FISP participation, for example gender of the household head).

In line with most agricultural surveys, data on agriculture production, consumption and other determinants of welfare, such as assets, was collected. Given the limited budget of the study, to save on costs and to avoid replication and farmer survey fatigue the primary raw dataset was obtained from the HarvestPlus/CIMMYT baseline survey, as it contained all the appropriate data meeting the objectives of this particular study. It is also important to stress that the researcher was amongst those involved in the design of the final questionnaire. Permission from both HarvestPlus and CIMMYT was obtained for this purpose.

PSM was used to compare the effect of FISP on its beneficiaries, while PCA was used to come up with a wealth index and thus compare the poverty profile of the treated to the untreated, as obtained from the FGT method. In addition to using yield as the outcome variable, the asset index was also used to ascertain the asset accumulation correlation with the FISP beneficiaries. To complement the results of PSM, the endogenous switching regression method was also utilised. These measures were appropriate for the study, as they could easily be used to make comparisons across FISP implementation.

4.1 SAMPLING DESIGN AND SELECTION

To ensure that all would-be respondents had an equal probability of being selected, the sampling method employed in the collection of data was two-step stratified sampling and simple random sampling. If the sampling design thus used by the survey was not stratified and clustered, it would have had an effect on the standard errors of the average treatment effect on the treated (ATT). The standard enumeration areas (SEAs) formed the first stage of the sampling units, while the households in each SEA formed the second-stage sampling units. The SEAs were sampled in proportional size to the respective AEZ, while a list of all households in the respective SEAs was obtained by the survey supervisors (one of whom was the researcher). A simple random sample of 10 households was selected based on the account that data was self-weighted. To minimise outright refusals and the incidence of respondents dropping out in the middle of the interviews, the point of entry into the SEA was local leadership who had to give consent for the survey to proceed, while the enumerators, once at household level, were mandated to introduce themselves and thoroughly explain the purpose of the survey and the estimated time to be taken to complete the interview.

The unit of analysis for the study was therefore rural Zambian households that were either FISP beneficiaries or non-beneficiaries – that is, all smallholder farmers who had planted maize in the 2010/2011 agricultural growing season in the Lusaka, Eastern, Central, Southern, Copperbelt and Northern provinces of Zambia. The survey focused on their agricultural production and their general livelihoods.

The main challenge across different types of impact evaluation is to find a good counterfactual – that is, the situation a participating subject would have experienced had he/she not been exposed to the programme. Fortunately, different methods have been designed that use varied sets of assumptions in accounting for potential selection bias in participation that might affect the construction of programme treatment effects (Khandker *et al*., 2010). Since the study used an existing dataset, the main challenge was to have a sample size with a percentage of untreated units large enough to allow for the possibility of estimating the impact of the treated on the treated.

In order to minimise the fundamental problem of causal inference arising from the absence of observed data for the treatment if not participating in FISP, a group of respondents had to be identified within the available sample. These respondents needed to be similar to the treatment group except for their participation in FISP, but this was not entirely possible because no two respondents could be the same. Therefore the study used only 347 treated observations and 150 untreated observations, giving a total sample of 497. This total sample size was arrived at by firstly cleaning the data from missing variables and outliers and then by controlling for all variables that were suspected to influence selection in FISP, while taking into account the problem of common support that might be introduced (inclusion of all variables affecting both FISP participation and the outcome variables). In this respect, the necessary precautions were taken to minimise the effects of a small sample size, as indicated by Busso, DiNardo and McCrary (2011). Also, during the preliminary analysis, the researcher deleted or dropped all observations with a propensity score lower than the minimum and higher than the maximum in the opposite group that were considered to have weak common support.

4.2 SURVEY INSTRUMENT

Although the actual survey instrument used by HarvestPlus and CIMMYT to collect data was lengthy and extremely detailed, this study made use of some appropriate subsections, namely:

Module A-Household identification
Module B-Household composition
Module CA-Land ownership

Module DA-General maize production

Module M-Household assets and housing conditions.

These subsections contained sufficient and appropriate data that was used to assess the impact of FISP without undermining the importance of minimising the biases associated with data collection, especially selection and information biases.

The first three modules provided data that was used to estimate PSM, while a combination of the third and fourth modules provided data that was used to address the first objective. The fifth module was used to calculate the wealth index and thus address the second and third objectives.

4.3 DATA COLLECTION

The data was collected between June and August 2011 by three teams, each comprised of a team supervisor and five enumerators that were recruited by HarvestPlus and CIMMYT from amongst final-year students in the Department of Social Work at the University of Zambia. The selected interviewers underwent five days of rigorous training, and a pre-test of the questionnaire was conducted before it was finalised so as to eliminate any possible errors that could affect the quality and accuracy of the data collected.

Furthermore, to avoid data entry biases, the survey instrument (questionnaire) was administered using a Personal Digitalised Assistant (PDA), and a completed questionnaire was later downloaded onto the computer directly as an Excel spreadsheet. Throughout the survey period, the interviewers were at all times in possession of clearly written data collection protocols for easy reference, as well as hard copies of the final questionnaire in the event of any malfunctioning of the PDA.

Although the original survey entailed the interviewing of 1 128 households, for purposes of this study, and after data cleaning, only 497 of the total households were included. The large number of households omitted from the final sample was mainly due to the data containing a large number of missing variables that could have affected the analysis and thus provide an inaccurate PSM estimation.

4.4 DATA ANALYSIS

The data collected from the study was transferred into Stata, and data cleaning was done by means of statistical summaries, such as measures of central tendency, so as to check for outliers and so on that might affect the analysis. Statistical analyses were done using both Stata version 11.0 and SPSS version 16.0. Cross-tabulations, frequencies and averages were also calculated. Poverty analysis was done using the Distributive Analysis Stata Package (DASP) version 2.2 (Abdelkrim & Duclos, 2007).

4.5 SOCIO-ECONOMIC CHARACTERISTICS OF RESPONDENTS

The study involved a total of 497 households across six provinces of Zambia, with about 85 % thereof being male-headed households with an average age of 48 years, and their female counterparts having an average age of 56 years. About 79 % of the respondents across all provinces were above the age of 35 years, and over 82 % of all respondents included in the study were able to read and write. On average 52 % had at least a primary education.

The average household size of 67 % of the respondents included in the study was seven members, while the average total land size owned by the respondents was 10.5 hectares. The average cultivated land was about 26 % of the total land owned, with over 46 % dedicated to maize cultivation. The average yield for maize was about 2.1 tons per hectare **(Table 4)**.

Table 4: General characteristics of respondents

Variable	Agro-ecological Zones								Full Sample	
	Zone II				Zone III					
	FISP	Std. Dev.	NON-FISP	Std. Dev.	FISP	Std. Dev.	NON-FISP	Std. Dev.	Total	Std. Dev.
Sample size	214		116		133		34		497	
Percentage distribution by gender of household head										
Male	85.0		84.0		86.0		85.0		85.1	
Female	15.0		16.00		14.0		15.0		14.9	
Average age distribution in years										
Male	48	15	46	15	49	16	48	16	48	15
Female	55	13	59	16	53	11	61	12	56	13
Age distribution										
Adult	79.4		75.9		80.5		76.5		78.7	
Youth	20.6		24.1		19.6		23.5		21.3	
Literacy level										
Cannot read or write	15.4		19.8		9.0		11.8		14.5	
Read only	3.3		6.9		0.8		2.9		3.4	
Read and write	81.3		73.3		90.2		85.3		82.1	
Level of education (years)										
Average education	7.70	3.67	6.31	3.09	8.30	3.15	6.97	3.20	7.48	3.45
Household size (average)										
Household size	7	3	6	3	6	3	7	3	6	3
Asset index	-1.06	1.27	-2.28	1.68	-0.16	2.00	-1.15	2.24	-1.11	1.82
Agricultural characteristics (averages)										
Land owned (ha)	9.20	22.28	5.45	8.36	17.7	103.91	8.28	12.26	10.54	55.98
Cultivated land (ha)	3.14	2.86	2.29	1.89	2.41	2.17	2.60	4.78	2.71	2.69
Maize area (ha)	1.48	1.42	1.29	1.02	0.94	0.81	0.95	0.87	1.25	1.18
Seed rate (kg/ha)	22.9	18.4	26.3	27.0	22.2	14.1	23.9	20.1	23.1	19.9
Basal fertilizer (kg/ha)	106	105	47	83	142	68	117	85	103	96
Top fertilizer (kg/ha)	106	111	49	78	143	69	104	85	102	98
Maize production (kg)	3126	4600	1768	3148	2495	2444	2193	3689	2576	3765
Maize yield (kg/ha)	2150	1347	1402	1159	2840	1403	1917	1358	2144	1414

Source: Author's calculations from survey data

4.6 FISP REQUIREMENTS / PREREQUISITES

FISP is presumably based on particular requirements for participation, as prescribed in the implementation manual of 2010/2011. The selection criteria stipulates that in order to participate in FISP, a farmer must belong to a registered farmer group, practise conservation farming, have at least five hectares of arable farmland of which at least 20 % must be cultivated, and must be able to apply fertilizer to the maize obtained from the programme.

Taking into account the above requirements, the results indicated that over 90 % of the 2010/2011 FISP beneficiaries belonged to a registered farmer group compared to less than 25 % of non-beneficiaries. Slightly more than 45 % of the beneficiaries were practising good agricultural practices (conservation farming) compared to less than 40 % of non-beneficiaries. It was also found that only about 25 % of beneficiaries had total arable land exceeding five hectares, with over 80 % cultivating more than one hectare, compared to less than 19 % of non-beneficiaries with land exceeding five hectares, of which only about 78 % were cultivating more than one hectare. The results also indicated that over 90 % of beneficiaries were using fertilizers (both basal and top) compared to less than 55 % of non-beneficiaries **(Table 5)**.

Table 5: Requirements for being a FISP beneficiary

	N=347	**N=150**
Requirement/Prerequisite	**FISP %**	**NON-FISP %**
Household member belonging to a registered farmer group	94.8	24.0
Good agricultural practices (conservation farming)	46.1	36.7
Farm size owned by household being above 5 ha	27.1	19.3
Total cultivated land of household being above 1 ha	86.5	78.0
Application of basal fertilizer by household	92.5	49.3
Application of top fertilizer by household	94.2	54.0

Source: Author's calculations from survey data

CHAPTER 6

RESULTS AND DISCUSSION

6.1 INTRODUCTION

This chapter presents the results obtained from various descriptive and regression analyses that were performed in order to meet the objectives of the study. Section 6.2 presents the PSM estimation using respondents' observable characteristics, which forms the basis for estimating the impact of the FISP intervention of agricultural productivity and asset accumulation. Section 6.3 presents and discusses the results for objectives 1 and 2, while section 6.4 checks the sensitivity of the estimated results with respect to unobserved influences. Section 6.5 provides the results from the endogenous regression method; section 6.6 presents and discusses the results for objective 3, and section 6.7 concludes the chapter.

6.2 ESTIMATION OF PROPENSITY SCORE RESULTS

The calculation of propensity scores to assess the '*with and without*' intervention on the FISP beneficiaries was based on the socioeconomic covariates related to households and household characteristics (household size, fertilizer application, land ownership and cultivation, type of crop variety used) and the agro-ecological zone in which the respondent's household was situated.

The results of a logit regression, which explains the probability of participation in FISP based on the propensity score, are presented in **Table 6.** The logit model fits the data reasonably well, as it has a McFadden r-squared of 0.18, which is more than the McFadden 10 % minimum threshold for the model to be satisfactory.

The participation regression suggests the importance of educational level, use of hybrid maize varieties, total cultivated land, and use of basal and top-dressing fertilizers in influencing participation in the FISP subsidy programme.

Table 6: Logit model estimates (propensity scores) of the decision to participate in FISP (Dependent Variable: FISP (1=Participation in FISP, 0=Otherwise))

Variables	**Estimate**	**Standard Error**	**z**	**P>IzI**
Gender of household head (1=male, 2=female)	-0.405	0.337	-1.20	0.229
Household size	0.0272	0.0457	0.60	0.550
Age of household head (years)	0.0416	0.0463	0.90	0.369
Age of household head (years) squared	-0.000317	0.000433	-0.73	0.464
Education level of household head (years)	0.0692**	0.0347	2.00	0.046
Use of hybrid maize variety (1=yes, 0=no)	0.537**	0.254	2.11	0.035
Total use of basal fertilizer (kg per ha)	0.0185***	0.00587	3.15	0.002
Total use of basal fertilizer (kg per ha squared)	-0.0000632***	0.0000168	-3.76	0.000
Total use of top fertilizer (kg per ha)	-0.00193	0.00461	-0.42	0.675
Total use of top fertilizer (kg per ha squared)	0.0000346***	0.0000118	2.93	0.003
Total land owned (ha)	0.0100	0.0137	0.73	0.465
Total land owned (ha squared)	-0.0000054	0.0000354	-0.15	0.879
Total cultivated land (ha)	0.327***	0.101	3.22	0.001
Total cultivated land (ha squared)	-0.0164***	0.00557	-2.95	0.003
Agro-ecological zone (1=Zone II, 0=otherwise)	-0.0958	0.272	-0.35	0.724
Constant	-2.696**	1.282	-2.10	0.036
Summary Statistics				
Number of observations	497			
LR Chi square (15)	110.05			
Probability>Chi square	0.000			
Pseudo R-squared	0.181			
Log likelihood	-249.336			

*Significant at 10 %, **Significant at 5 %, ***Significant at 1 %

Source: Author's calculations from survey data

In order for the study to continue discussing the causal effect of FISP participation with confidence, the quality of the matching process was analysed with regard to the common support condition. This was done by visual inspection of the densities of propensity scores of the treated and non-treated groups. The common support assumption was satisfied in the region of [0.18358294, 0.99955514]. **Figure 5** supports the result that there was a good overlap in the distribution of the propensity scores of both the participants and the non-participants. From the graph, on the x-axis, the upper half shows the propensity score distribution for the treated, while the lower half refers to the untreated respondents and the y-axis indicates distributional frequency of the propensity scores.

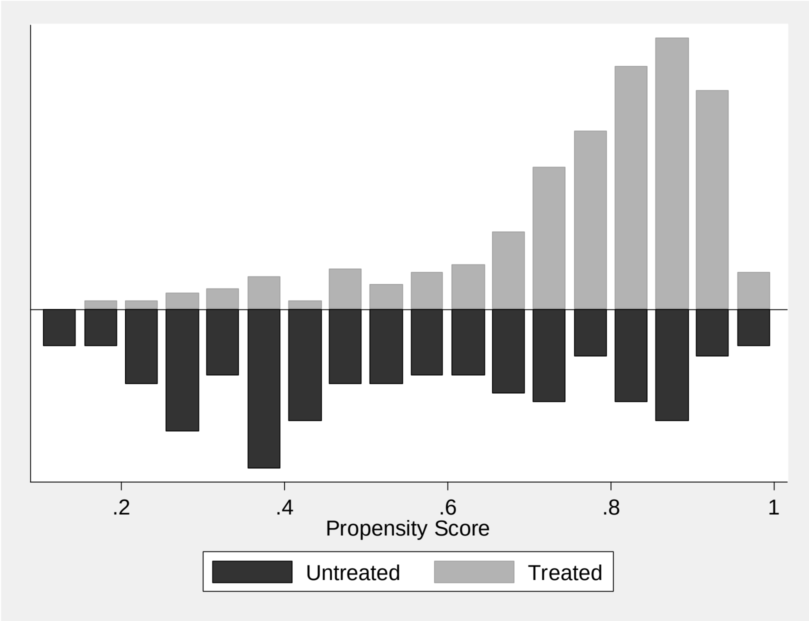


Figure 5: Propensity score distribution and common support for propensity score estimation

Source: Author's calculations from survey data

6.3 IMPACT OF FISP ON MAIZE YIELD AND ASSET ACCUMULATION RESULTS

For the study to meet the first two objectives, the average participation effects (ATT), which is the average gain from participating in FISP, was calculated, of which the outcome variables were maize production per hectare (maize yield) and asset index (wealth index calculated using the PCA procedure) as proxy for asset accumulation. To check for robustness of the results within the PSM approach, four matching algorithm methods were used and compared, namely Nearest Neighbour (NN), Radius (RM), Kernel[6] (KM) and Stratified (LRM). **Table 7** shows the estimates of participation effect (ATT) from the four matching algorithms obtained, using the psmatch2 command in Stata 11. The results indicated that 2010/2011 FISP participation significantly increased maize yield and asset accumulation. The increase in maize yield ranged from 424 kg/ha to 457 kg/ha. Although this estimated incremental yield of 440 kg/ha is below the average maize yields for AEZ II (1887.1 kg/ha) and AEZ III (2651.9 kg/ha) as observed in this survey, this is equivalent to a monetary gain ranging from US$ 145[7] to US$ 157 per hectare of maize produced when the household sells to the Food Reserve Agency (FRA), which is currently the major maize buyer at a floor price of

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[6] Particularly the ATT from kernel matching are considered to be very useful at bias reduction.
[7] The 2011 official exchange rate averaged about 3 500 Zambian Kwacha per US$ 1.

1,200 Zambian Kwacha per kilogram. Under small-scale conditions, this money is probably sufficient to enable the households to acquire some assets as depicted in the positive ATT on asset index.

Table 7: Impact of FISP on beneficiary household maize yield and asset index

Matching algorithm	Outcome variable	Means of outcome variables		ATT
		Adopters	Non-adopters	
NN	Maize yield (kg/ha)	2418.8	1960.96	457.84** (2.16)
	Asset index	-0.72	-1.18	0.46* (1.68)
RM	Maize yield (kg/ha)	2418.8	1988.16	430.64** (2.34)
	Asset index	-0.72	-1.10	0.38 (1.16)
KM	Maize yield (kg/ha)	2414.25	1990.74	423.51*** (2.64)
	Asset index	-0.72	-1.20	0.48* (1.87)
LRM	Maize yield (kg/ha)	2414.27	1967.04	447.20** (2.44)
	Asset index	-0.72	-1.21	0.50 (1.59)

Notes: Absolute value of Z-statistic in parentheses
Bootstrapped standard errors using 50 replications of the sample
*Significant at 10 %, **Significant at 5 %, ***Significant at 1 %
Source: Author's calculations from survey data

6.4 SENSITIVITY ANALYSIS: ACCOUNTING FOR UNOBSERVED HETEROGENEITY

The results from the Rbounds indicated that although it can be stated with reasonable confidence that a causal relationship was found to exist between participation in FISP and maize yield, as well as between participation in FISP and asset accumulation, when there was unobserved cofounding variables, the results also confirmed the existence of individuals who were participating in FISP but failed to meet the prerequisites, as shown in **Table 5**, due mainly to political influences that in turn affected programme administration – that is, because of different values on an unobserved covariate (about 30 %), despite being identical on the matched covariates, the inference could be affected. With that in mind, **Table 8** shows that the null hypothesis of no effect of FISP participation on yield and asset accumulation was not plausible. This therefore signifies that the results were quite insensitive to unobserved covariates – that is, on maize yield, endogeneity characteristics would have to increase the odds ratio (gamma) by a factor of 1.4 (40 %) for the inference on the impact of participation in FISP on the maize yield to be ignored.

Similar to the findings noted by Kassie, Shiferaw and Muricho (2010), Rbounds critical values of 1.4 and 1.2 do not mean that unobserved heterogeneity existed and that participation in FISP had no effect on maize yield or asset accumulation. This only implies that the confidence interval for the effect would include zero if an unobserved variable caused the odds ratio of participation to differ between participant and non-participant groups by a factor of 1.4 for yield and 1.2 for asset accumulation. In summary, the Rbounds results indicate that the ATT estimates that were obtained **(Table 7)** were as a result of participation in FISP.

Table 8: Sensitivity analysis with Rbounds. Treatment=participation in FISP

Gamma	Yield		Asset Accumulation	
	sig+	sig-	sig+	sig-
1	2.90E-06	2.90E-06	0.000602	0.000602
1.1	8.30E-05	5.60E-08	0.006718	0.00003
1.2	0.00105	8.60E-10	**0.037726**	**1.10E-06**
1.3	0.007225	1.1E-11	0.126726	3.50E-08
1.4	**0.030994**	**1.2E-13**	0.289416	9.10E-10
1.5	0.091895	1.2E-15	0.496255	2.10E-11
1.6	0.203806	0	0.691836	4.10E-13
1.7	0.360091	0	0.836708	7.50E-15
1.8	0.533671	0	0.924264	1.10E-16
1.9	0.692634	0	0.968856	0
2	0.816209	0	0.988497	0

gamma - log odds of differential assignment due to unobserved factors
sig+ - upper bound significance level (overestimation of treatment effect)
sig- - lower bound significance level (underestimation of treatment effect)

Source: Author's calculations from survey data

6.5 ENDOGENOUS SWITCHING REGRESSION ESTIMATION RESULTS

To further check the robustness of the estimated results obtained from the PSM model in evaluating the impact of FISP on maize yield and asset accumulation, the endogenous switching regression (ESR) approach was used. Besides the ESR complementing the PSM, it was also used to estimate the effect of unobservable characteristics on the decision to participate in FISP. The ESR estimated two separate equations for FISP participants and non-participants besides the selection equation (see Gitonga, De Groote, Menale & Tefera, 2012; Kuntashula & Mungatana, 2013; Shiferaw, Kassie, Jaleta & Yirga, 2013). The estimates from ESR were used to compute the expected values in the actual and counterfactual conditions in terms of the average treatment effect on the treated (ATT) and untreated (ATU) by comparing the respective expected values of the outcomes of FISP participants and non-participants.

Table 9 **presents the results of the ESR for the expected maize yield and asset accumulation under actual and counterfactual conditions. The last column of**

Table 9 shows that both FISP participants and non-participants would benefit from participating in FISP in terms of increased yield and asset accumulation, although non-participants would benefit most from participating in FISP with regard to accumulating assets, compared to actual participants. Participating in FISP therefore increases the probability of higher maize yields and the accumulation of assets, thus improving the household's ranking on the wealth index.

Households participating in FISP would have had a maize yield of about 488 kg per hectare less had they not participated in FISP (ATT), while households not participating in FISP would have had a maize yield of about 166 kg per hectare more if they had participated in FISP (ATU). Similar results were also obtained using the asset index as an outcome variable, where participation in FISP increased the chance of accumulating assets 1.1 times for FISP participants and 1.6 times for non-participants, had they participated in FISP. These results imply that, ceteris paribus, the current non-participants would have realised higher levels of maize yields and asset accumulation from switching to participation in FISP.

Table 9: Endogenous switching regression estimates for yield and asset index outcomes

	Decision Stage		Average Treatment Effects
	To participate	Not to participate	
Yield in kg per hectare			
FISP Participant	2412.11(37.48)	1924.37 (45.91)	ATT=487.74 (47.17)***
FISP Non-Participant	1696.17(65.45)	1529.46 (63.42)	ATU=166.70 (41.71)***
Asset Index			
FISP Participant	-0.7155(0 .0244)	-1.8261(0.0455)	ATT=1.11(0.0345)***
FISP Non-Participant	-0.4156(0.0463)	-2.0099(0.0692)	ATU=1.60(0.0494)***

ATT average treatment effect on the treated (participated–had not participated), ATU average treatment effect on the untreated (had they participated–not participated)
*Significant at 10 % **Significant at 5 % ***Significant at 1 %
Source: Author's calculations from survey data

6.6 POVERTY RATE LEVELS BETWEEN FISP BENEFICIARIES AND NON-BENEFICIARIES

The calculation of the wealth index using PCA was twofold: Firstly, the index was used to account for different asset possession levels of the respondents, and secondly the index was used as a proxy for the resource poverty level of each respondent with the aim of testing whether the level of poverty differed between FISP participants and non-participants.

The results shown in **Table 10**, using the asset index where 0 was a cut-off point, indicated that FISP participants were better off by 9.8 percentage points than the non-participants in terms of capital resources. These results are highly comparable to the CSO (2012) rural poverty headcount rate of about 78 %. It was further noted that female-headed households (83.9 %) were more resource capital poor than male-headed households (73.9 %), while AEZ II comprised more respondents (86.8 %) who were resource capital poor than AEZ III (50.4 %).

Although the FGT poverty measure results also indicated that FISP participants had on average lower poverty levels than non-participants, the values obtained were significantly lower than the CSO values. This might be due to differences in the calculation methods used.

Overall the results indicated that the incidence of poverty, depth of poverty and severity of poverty were lower among participants in the 2010/2011 FISP than among non-participants. These results were also in line with the findings of Sarris *et al.* (2006) obtained in Tanzania and of Jayne *et al.* (2011) obtained in Malawi.

Table 10: Poverty levels of FISP beneficiaries and non-beneficiaries (indicators of poverty for FGT = total cultivated land with a poverty line set at 50 % of the mean value)

FGT & PCA Poverty Measures	**Observed from survey data (%)**			**CSO* Rural Poverty Levels (%)**
	FISP	**Non-FISP**	**All**	**National**
Poverty headcount rate	26.8	36.7	29.5	78.0
Intensity of poverty (GAP)	11.2	15.7	12.5	44.0
Severity of poverty Index	5.8	8.3	6.5	30.0
Asset Index from PCA	72.3	82.2	75.1	-

*CSO utilises the basic food basket adjusted with price updates and Engel ratios
Source: Author's calculations from survey data

6.7 CONCLUSION

The results presented above are in line with the common premise that input subsidies have a direct positive impact on agricultural productivity and asset accumulation and, to some extent, a positive indirect effect on poverty reduction.

CHAPTER 7

CONCLUSIONS AND POLICY IMPLICATIONS

7.1 CONCLUSIONS

The study evaluated the impact of participation in the Farmer Input Support Programme (FISP) on maize yield and asset accumulation in Zambia's agro-ecological zones two and three. To account for observed participation bias, a propensity score matching (PSM) approach was used, while sensitivity to unobserved participation effect was checked using the Rosenbaum bounds procedure and, to ensure result robustness, the models were complemented with the endogenous switching regression model. The poverty levels of FISP participants were also checked using principal component analysis (PCA) and the common Foster-Greer-Thorbecke (FGT) poverty indices, with total cultivated land as a plausible welfare indicator.

The results indicated that participation in FISP in 2010/2011 was associated with higher maize yields and the accumulation of more assets than non-participation. The results were also quite insensitive to unobserved selection bias. Furthermore, it was observed that participation in FISP could be presumed to contribute to participants being more affluent than non-participants.

The positive impact of FISP on the maize yields and asset accumulation of participating farmers therefore allowed the study to reject the null hypotheses of no effect of FISP participation on yield and asset accumulation and thus poverty levels. It also justifies government's continued implementation of FISP, as participation significantly improves the livelihood of households. The results are also consistent with the perceived benefits of FISP, with most studies having found that poorer farmer households are not only less productive, but also possess fewer assets.

7.2 POLICY IMPLICATIONS

In order for the subsidy programme to achieve significant results in terms of productivity and asset accumulation, there is a need for a deliberate policy to be devised to target poor households. This would also ensure enhanced maize productivity and increased asset accumulation for poor rural farmers. Furthermore, making it mandatory for the subsidy programme to include the promotion of appropriate technologies that enhance agricultural productivity, or for there to be investment in farmer extension support and education programmes, could help small-scale farmers to overcome most of their livelihood challenges. The study findings therefore support the emphasis on designing smart subsidy policies that will address both agricultural productivity and poverty reduction.

7.3 AREAS OF FUTURE RESEARCH

Since instrumental variable (IV) regression methods could be used to control for unobserved bias in matching estimators, it would be interesting for future research to utilise PSM, ESR and IV regression for analysis purposes. This could be successfully applied, especially in extremely large samples where IV estimators are believed to be less biased. In light of the fact that most subsidy programmes in Africa (Zambia included) may have selection bias mainly due to political influences, it could be effective to use a method that would account for this, such as the difference-in-difference estimator, perhaps in combination with matching, in order to reduce bias and better describe the effect of treatment on outcomes.

Since the study was unable to link FISP to poverty reduction due to the absence of benchmark poverty indices for FISP participants, an opportunity exists for a study to be conducted on the impact of FISP on poverty reduction by benchmarking the analysis of the welfare effects of the programme to some base year so as to demonstrate the transition movement in and out of poverty as a result of FISP.

Finally, for purposes of future work, it would probably be best to increase the control group to at least the same size as the treatment group, since a certain number would be discarded in any case.

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