An economic evaluation of the Cotton Yield Programme in Zambia

by

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DECLARATION

I, James Ngulube, declare that the thesis, which I hereby submit for the degree of Master of Sciences in Agricultural Economics at the University of Pretoria

a) Represents my own work;
b) Has not previously been submitted by me for a degree at this or another University; and
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APPROVAL

This dissertation of James Ngulube has been approved as partial fulfilment of the requirement for the award of the degree of Master of Science in Agricultural Economics by the University of Pretoria.

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ABSTRACT

This study evaluates the economic impact of the Cotton YIELD Programme on the agricultural income of smallholder cotton farmers in Zambia. The analysis was based on pooled cross-section data of 300 cotton farmers, collected from two (2) household surveys, who were randomly selected in Mumbwa district in Zambia during the 2005 and 2015 agricultural seasons. The study utilised Propensity Score Matching (PSM) methods to account for observable heterogeneity in characteristics between participants and non-participants of the Cotton YIELD Programme, and the Double Difference (DD) method for unobservable characteristics between the two (2) groups. The PSM was used to obtain matched observations of participants and non-participants, based on observed characteristics. The results suggest that years of education, farm size, membership of local farmer organisation, assets value, access to credit, and ownership of animal traction positively influence smallholder farmers' participation in the Cotton YIELD Programme. However, distance to extension agents and market outlets negatively influence smallholder farmers' participation. The study found that the Cotton YIELD Programme has significantly increased the agricultural net income of the participants by 38.1 %. The positive and significant impact of the Cotton YIELD Programme on agricultural income is consistent with the perceived role of improved technologies in increasing agricultural net income. This study supports broader investment in agricultural research to address developmental challenges. However, reaching more smallholder cotton farmers with the Cotton YIELD Programme may require policy support for improving access to extension services and market outlets that stimulate participation.

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CHAPTER 1
INTRODUCTION

1.1 Background

Rural poverty worldwide remains a challenge. In Zambia, the current levels of rural poverty are extremely high.[1] Recent statistics indicate that urban poverty seems to be slowly decreasing, while rural poverty is persistently high, in approximately at 77 % of total rural households (Central Statistical Office [CSO], 2010). To address the poverty problem, several strategies are well documented on how to remedy and alleviate the issues giving rise to poverty (World Bank, 2008; International Fund for Agricultural Development [IFAD], 2001). Recommendations from IFAD and World Bank over the years have included topics on improving access to productive assets, inclusiveness, making markets work for the poor, and agricultural productivity growth via improved inputs (IFAD, 2001; IFAD, 2011; World Bank, 2012). Among the many recommendations from these reports, of particular relevance to this study is the subject of productivity growth via improved input usage and access to functional markets.

In most developing countries, functional markets are underdeveloped. Consequentially, smallholder farmers have almost no access to seasonal credit to finance input purchases (Kirsten *et al.*, 2009). Out-grower schemes comprise one of the ways through which smallholder farmers gain access to markets and improved inputs. The out-grower schemes provide inputs on credit to the rural smallholder farmers who mainly face financial constraints in purchasing improved inputs, and in return, provide markets for the crop output (Lozano, 2012). In Zambia, one of the most important cash crops grown via out-grower schemes is cotton. The cotton out-grower scheme has undergone various transformations since 1994, from a parastatal monopoly to a competitive private enterprise (Tschirley & Kabwe, 2009). These transformations have led to new entrants, aggressive competition in the purchase of seed cotton, recruitment of farmers to grow cotton, and increased seed cotton

1 Rural poverty is defined as economic and/or social deprivation of the rural households (CSO, 2010). Many poverty assessments use income shortfall approaching when measuring poverty, as the concept directly relates to income deprivation (United Nation Development Programme [UNDP], 2005). The approach is appealing since the ability to acquire nearly all basic needs depends on household income.

production. However, seed cotton productivity (yield per hectare) at farm level has remained low, resulting in low agricultural net income (Ministry of Agriculture and Livestock [MAL], 2013). One of the major out-grower players in the cotton industry is Dunavant Zambia Limited (DZL)[2], which has contracted about 170 000 smallholder farmers (Lozano, 2012).

In 2005, DZL with funding from the German Development Agency (GTZ), introduced a programme called ‘Yield Improvement through Empowerment, Learning and Discipline’ (YIELD) in the Eastern, Southern, Lusaka and Central provinces of Zambia. The programme is also part of the “Cotton Made in Africa” project (Tschirley & Kabwe, 2009). The programme is embedded in the principles of empowerment, learning and discipline, which aim at increasing agricultural net income of smallholder cotton farmers through increased productivity (yield per hectare). The Cotton YIELD Programme is a package of improved technologies and practices, namely early and proper land preparations, timely planting, correct and properly spaced plant population, effective weed management, and integrated pest management. The transfer and adoption of improved agricultural technologies of the programme have been achieved through training conducted by DZL agricultural specialists. The Cotton YIELD Programme has had about 42 000 beneficiaries (DZL, 2015).

Although it is expected that by adopting improved technologies of the Cotton YIELD Programme, cotton productivity would rise, translating in improved agricultural net income of the beneficiaries, the impacts of programmes promoting improved technology on agricultural income over the past decades have been mixed (World Bank, 2006). Some studies show positive impact on agricultural income (for example, Davis *et al.*, 2003; Haggblade *et al*., 2011; Simtowe *et al.,* 2012; Muhammad *et al.,* 2013; Mendola, 2006; Nyanga *et al.*, 2011). Yet, others indicate no significant impact (Ndoro *et al*., 2014; Feder *et al.*, 2006; Hossain *et al.*, 2003). Therefore, it is not clear if the Cotton YIELD Programme has increased the agricultural net income of smallholder cotton farmers in Zambia, as no rigorous assessment of the programme’s impact on agricultural income, over a reasonable period of time, has been conducted. Furthermore, the factors that determine participation in the programme are poorly understood, thus calling for further research. There are also key questions relating to cotton’s agricultural income potential via productivity growth and scale-

2 Dunavant Zambia Limited (DZL) is now called NWK Agri-Services Zambia Limited.

up, as DZL intended to increase the number of beneficiaries to 100 000 by 2016 (DZL, 2015). Therefore, this study seeks to address this knowledge gap on the impact of the programme by evaluating the impact of the Cotton YIELD programme on smallholder farmers' agricultural net income, as well as identifying the factors that influence participation. The theoretical underpinning of productivity via a programme such as Cotton YIELD is also discussed.

1.2 Problem Statement

The goal of the Cotton YIELD Programme is to increase the agricultural income of smallholder cotton farmers through increased cotton productivity (yields per hectare). However, little is known about the impact of the Cotton YIELD Programme on the agricultural income of smallholder cotton farmers in Zambia. A study by Tschirley and Kabwe (2009) on the cotton sector of Zambia reported that monitoring data from DZL suggested that cotton farmers who had adopted improved technologies of the programme had achieved average yields of 788 kg/ha compared with 538 kg/ha for non-adopters. However, Peltger and Rottger (2013) observed that higher cotton productivity achieved by adopters of improved technology did not always translate into higher agricultural net income because additional yields did not always compensate for the increase in costs. Therefore, a further examination of the impact of the Cotton YIELD Programme on agricultural income is warranted, as it is not clear if the Cotton YIELD Programme has increased agricultural net income per participant cotton farmer.

In addition, earlier studies (for example, Haggblade *et al.*, 2010; Nyanga *et al.*, 2011) on whether technology transfer programmes had contributed to increased agricultural net income in Zambia did not account for endogeneity or econometric problems that arise when the selection of farmers and programme placement are not randomly done. These econometric problems (observable and unobservable heterogeneity in characteristics) might have resulted in biased conclusions about the impact of improved technology transfer programmes in Zambia. To avoid such potential pitfalls, an impact estimation strategy pursued in this study uses the Double Difference (DD) method, combined with Propensity Score Matching (PSM) methods. This study, by evaluating the impact of the programme, would, therefore, contribute to reducing the knowledge gap on the impact of the Cotton YIELD programme being implemented by DZL on the agricultural net income.

1.3 Research Objectives

The general objective of this study is to evaluate the impact of the Cotton YIELD Programme on the income of smallholder cotton farmers in Zambia.

The specific objectives of the study are:

a) To determine whether the Cotton YIELD Programme has increased the agricultural net income of the smallholder cotton farmers.
b) To identify factors that influence smallholder cotton farmers' participation in the Cotton YIELD Programme.

1.4 Hypotheses

a) The null hypothesis is that the Cotton YIELD Programme has not increased the agricultural income of the smallholder cotton farmers. The alternative hypothesis is that the Cotton YIELD Programme has increased the income of the smallholder cotton farmers.
b) The null hypothesis is that socio-economic and demographic factors do not influence smallholder farmers' participation in the Cotton YIELD Programme. The alternative hypothesis is that the socio-economic and demographic factors do influence smallholder farmers' participation in the Cotton YIELD Programme.

1.5 Significance of the Study

Given that rural poverty is persistently high, at approximately 77 % of total rural households in Zambia (CSO, 2010), and that there are over 350 000 cotton farmers representing 15 % of the total farm households in Zambia (Lozano, 2012), the significance of cotton income in rural poverty reduction cannot be underestimated. If the specific objective in 1.3.b above is met, namely the factors that influence smallholder farmers' participation in the Cotton YIELD Programme are identified, and should participation be proven conducive in increasing agricultural net income, then this study could improve on the decision dynamics of the involvement of smallholder farmers in YIELD Programme. The study could also help to better understand what determines participation in the YIELD Programme, as well as improving the targeting of the programme. Moreover, an understanding of the programme's impact on agricultural net income of smallholder farmers would provide rationale for a scale up. In addition, it would also bring to light the poverty-reduction potential of cotton production via productivity growth, given the importance of agricultural growth in poverty reduction.

1.6 Organisation of the Dissertation

This dissertation is organised as follows. Chapter 2 describes the literature review, which comprises discussion of existing empirical evidence on impacts and factors affecting participation. Chapter 3 describes the theoretical framework and conceptual framework. Chapter 4 describes the study area, data collection and sampling procedure, analytical approach and data collection limitations. The results of the study are discussed in Chapters 5 and 6.

CHAPTER 2
LITERATURE REVIEW

This chapter begins by discussing the macro cotton sector reforms in Zambia. It reviews the previous work on the impact of agriculture technology/participation and factors affecting participation in programmes such as the Cotton YIELD Programme.

2.1 Macro Cotton Sector Reforms in Zambia

The cotton industry in Zambia has undergone various transformations, from a parastatal monopoly to a competitive private enterprise. The sector was dominated by the Lint Company of Zambia (LINTCO), a parastatal company which provided inputs to farmers between 1977 and 1994 (Tschirley & Kabwe, 2007). Lint Company of Zambia enjoyed both monopoly powers in providing inputs to farmers on credit and monopsony in buying seed cotton in the industry. However, in 1994 the company was privatised and Lonrho and Clark Cotton bought its ginneries. The two companies initiated out-grower schemes and competition was not very aggressive, as they operated in different provinces of Zambia. Lonrho operated in the Eastern and Central provinces, with Clark in the Southern and Lusaka provinces. In 1997, more players entered the industry, both in assembly and ginning. The firms competed aggressively in the purchase of seed cotton and recruited farmers both directly and indirectly. The indirect recruitment was conducted through agents who were contracted by the ginners. Independent cotton traders also emerged in the sector and distributed inputs to cotton farmers, bought the output and sold to ginners of their choice.

The Zambian Government then committed to a liberalising the cotton sector and made no attempt to limit competition in the sector. As a result, many problems emerged. Firstly, the total ginning capacity increased to about 150 000MTs in 1998, while production peaked at over 105 000MTs, but less than 150 000MT (Tschirley & Kabwe, 2009). This overcapacity created a scramble for seed cotton among actors in the sector with a view to reducing ginning costs and consequently increasing output. The emergence of a group of independent cotton traders also contributed to the scramble for seed cotton. Some ginners offered higher prices to farmers, while others did not. This resulted in farmers behaving in an opportunistic manner (side selling) by selling the crop to ginners that did not contract them to grow cotton. This made loan recoveries difficult for some, and many players experienced increases in loan default rates. For instance, Lonrho reported that its loan recovery rate had declined from 86 % in 1996 to 65 % in 1999 (Tschirley & Kabwe, 2007).

These problems were further exacerbated by continued declines in world market prices for cotton lint from their peak in 1995, and the risks were transferred to the farmers. Furthermore, farmers were used to increasing seed cotton prices and with limited market information found it difficult to understand the decline in seed cotton prices. Lack of transparency in the setting of seed cotton prices and deductions of input costs contributed to the belief by stakeholders that farmers were being exploited by ginners. These mistrusts led the sector experiencing the biggest crisis in 1999 when the cotton business of Lonrho, the biggest player in the sector, was sold to DZL. In addition, the numbers of contracted farmers were cut back and production volumes declined to less than 50 000MTs (Tschirley & Kabwe, 2007). In 2005, the sector faced another crisis attributable to the appreciation of the Zambian currency (Kwacha) which made the country's cotton lint exports unattractive on the international markets, resulting in low domestic producer prices for seed cotton. Cotton production declined by 40 % and by as much as 50 % in the following season of 2006/07 (Tschirley & Kabwe, 2009). However, the sector recovered after DZL launched its distributor and credit repayment systems.

Although Zambia's seed cotton production increased from 30 000 metric tons in 1995 to 100 000 metric tons in 2007, productivity (yield per hectare) at farm level remained low, with a national average varying between 450kg/ha and 700kg/ha, resulting in low agricultural net income (Tschirley & Kabwe, 2007). The low yield per hectare had been attributed to low technology adoption rates and inadequate funding given to agriculture extension services (Ministry of Agriculture and Livestock [MAL], 2013). Funding of agriculture extension services has been declining since the 1990s. As a result, the extension worker to farmer ratio has risen to 1: 900, higher than the recommended ratio of 1:400, and the quality of extension services had declined (MAL, 2013). Despite the increase in cotton production and the numbers of smallholder farmers engaged in cotton farming, rural poverty levels have remained persistently high (CSO, 2010). The persistently high poverty levels in largely agrarian societies such as in Zambia are a result of low agricultural incomes (MAL, 2013).

According to Haggblade *et al.* (2007), agricultural growth contributes to poverty reduction in three ways. Firstly, it increases agricultural incomes of the majority of the rural households who work in agriculture; secondly, it reduces food prices; and thirdly, it stimulates growth linkages with other sectors of the economy.

2.2 Existing Empirical Evidence on Determinants of Adoption/Participation

Several new technology transfer programmes have been implemented in sub-Saharan Africa (SSA), and Zambia in particular, to accelerate the diffusion of new technologies. However, the adoption rate of new technologies has remained relatively low (MAL, 2013; Peterman *et al.,* 2010). Adoption is defined as an integration of new technology into farmers' normal farming activities over a period of time (Feder *et al.,* 1985). A number of studies have been conducted to examine factors that influence smallholder farmers' participation in technology transfer programmes (For example, Simtowe *et al*., 2012; Nell *et al.*, 1999; Fisher & Kandiwa, 2013). Nevertheless, the results are mixed and conflicting.

In Malawi, Simtowe *et al*. (2012) examined whether demographic characteristics affected new technology adoption decisions. The study noted that the age of the household head influenced adoption decisions of new technology negatively, suggesting that older farmers were less likely to adopt new technologies. Literature on adoption shows that the exact effect of age on adoption decisions is ambiguous, as young farmers, despite having lower risk aversion behaviour, might have less farming experience (Ng'ombe, 2013). Therefore, the negative effect of age on adoption decisions could be explained in terms of the risk aversion paradigm that farmers considered new technology to be riskier than old technology. However, Awotide *et al.* (2012) found that the age of a farmer had no significant influence on adoption decisions of new technologies in Nigeria. Furthermore, the study found that the majority of farm households were middle aged, hence the age of the decision maker had no significant influence on adoption decisions of a package of technologies. Similarly, in Uganda, Kassie *et al.* (2011) also observed that the average age of the household head had no significant influence on modern technology adoption decisions. Doss and Morris (2000) reported that gender and marital status of the household head could be linked to factors that indirectly influence participation decisions. The study further found that extension agents preferred to visit male headed and married households, as they had larger farm sizes and better access to labour for adopting new technologies, compared with female headed and single households. Fisher and Kandiwa (2013) also reported that asset poor households in Malawi, who were mostly female headed and single households, were less likely to adopt new technology. The results correspond with Peterman *et al.,* (2010) and the World Bank's (2012) findings that in developing countries, female headed and not married households had less access to technology than their male counterparts did, hence are less likely to adopt new technologies. However, the gender differences in new technology adoption decisions disappeared once controlled for access to land, labour, extension services and markets (Chirwa, 2005; Doss & Morris, 2001; Smale, 2011).

Elias *et al.* (2013) reported that education was a determinant of farmers' adoption decisions of new technology. This is because education enhances farmers' abilities to understand the benefit of improved technology and to interpret and modify extension information. The results are consistent with observations by Foster and Rosenzweig (2010) as cited in Fisher & Kandiwa's (2014) report, as well as Rubas (2004). Rubas (2004) worked on universality of farm size, education, extension services, and age in adoption of new technologies. The study reported that education encouraged the adoption of all types of technologies, irrespective of location, whereas age did not influence adoption decisions of all types of technologies. However, Mendola (2006) found contrasting evidence that education had no significant influence on adoption decisions of improved technologies in Bangladesh. Similarly, Awotide *et al.* (2011) found that education had no significant influence on adoption decisions of improved technologies, although no plausible explanations were given for the contrasting findings.

Langyintuo and Mungoma (2008) examined whether wealth and farm characteristics influence technology adoption decisions. The study observed that farmers that had more wealth had higher risk-bearing abilities and were, therefore, more likely to adopt new technologies. Similarly, Kassie *et al.* (2011) in Uganda found that progressive farmers, in comparison with other farmers, had greater asset values and larger farm sizes and were more likely to adopt new technologies. The results are consistent with Fisher and Kandiwa's (2013) observations in Malawi that asset-poor farm households had no financial resources to adopt the modern technologies of the agricultural input subsidy programme. The researchers suggested that cash transfer interventions could accelerate adoption of the modern technologies of the agricultural input subsidy programme among asset-poor farmers in Malawi. Nevertheless, Mendola (2006) found no significant association between farm size and new technology adoption decisions in rural Bangladesh. In addition, Asfaw and Shiferaw (2010) and Kassie *et al.* (2011) in Uganda also argued that off-farm income had no significant effect on the adoption of new technology decisions. The study further recommended ownership of either radios or television sets or mobile phones among farmers so as to accelerate adoption of new technologies, as the access to media facilitates farmers' access to information regarding new technologies.

Becerril and Abdulai (2010; 2009) analysed land size distribution between adopters and non-adopters of new technology and saw significant differences. Adopters had larger farm sizes than non-adopters did, suggesting a positive association between farm size and new technology adoption decisions. The results correspond with Rubas' (2004) findings and are supported by the finding of Darr and Chern (2000) that larger farm sizes encouraged adoption of all types of technologies, irrespective of location. This is because farmers with larger farm areas are considered progressive farmers with more risk-bearing ability (Doss & Morris, 2001; Place & Otsuka, 2001). Mendola's 2006 study found that family size and number of adults in a household had a positive effect on new technology adoption decisions. Although Mendola's (2006) observations support the importance of family labour in the adoption of new technology, the International Labour Organization [ILO] (2013) observed that a large family size had no effect on modern technology adoption decisions. This is because households that have a larger family size tend to have more members below the age of 15 years, who by child labour laws are not allowed to work on the farms (ILO, 2013). Therefore, whether family size and other demographic characteristics influence adoption decisions remains an empirical question to be investigated in this study.

Davis (2008), Marra *et al*. (2004) and Kassie *et al.* (2011) investigated whether institutional and access-related factors affect adoption decisions of new technology. The studies observed that a higher proportion of adopters were members of local institutions and were nearer to information and market centres than non-adopters were. Beaman and Dillon (2014) reported that membership of local farmer organisations influenced participation decisions positively, as members share experience and information. Furthermore, the study found that social networks, through local institutions such as co-operatives, were reinforcing extension messages and uptake of new technologies. As a result, extension workers often targeted social groups in the diffusion of new technology as the strategy was not only cost effective but also less labour intensive. The findings are in agreement with the observations of Aldana *et al.* (2010) that individual farmers initially experimented with new technology in isolation, but the adoption of new technology increased as information became clearer through mutual sharing and comparison of own results and experiences between neighbours.

In South Africa, Nell *et al.* (1999) identified distance to extension agents and markets as factors that negatively affect adoption of new technologies. The study found that farmers who lived nearer to extension agents and market outlets were more likely to adopt new technologies as they had more access to information and incurred less transport costs than those who lived far did. Therefore, new technologies were more profitable to farmers who were nearer to extension agents and market outlets than those who were farther away due to opportunity costs of accessing information owing to position. Gerhart's (1975) study in Kenya reported that access to credit and extension services encouraged adoption of new technologies. Extension services improve farmers' resilience in adopting recommended agricultural technologies which result in increased agricultural net income in the long term. However, Rubas (2004) showed that access to extension services did not encourage adoption of all types of technologies due to non-simplification of extension messages, making diffusion of new knowledge less effective.

Although past studies provide useful information on factors influencing adoption decisions of improved agricultural technologies, no clear-cut picture has developed, as the observations on factors affecting adoption of improved agricultural technologies are mixed and contrasting. These conflicting findings called for further investigation into whether the socio-economic and demographic factors influence smallholder cotton farmers' participation in the Cotton YIELD Programme in Zambia.

2.3 Discussing Existing Empirical Evidence on Impact

Although several improved technology transfer programmes have been implemented in SSA, the effects of these new technologies have been mixed and conflicting (World Bank, 2006). Application of linear programming methods to optimise crop income (Haggblade *et al*., 2010) indicated that improved agricultural technologies increased agricultural incomes of poor cotton farmers with more access to cash inputs by 140 %, as compared with 40 % of households with less access to cash inputs. Furthermore, the study identified major constraints to improved technologies adoption as being a lack of access to labour, land, animal traction and finance. Recent studies (for example Simtowe *et al.,* 2012; Muhammad *et al.,* 2013; Kassie *et al.*, 2011) observed that adoption of improved agricultural technologies had a positive impact on the incomes of farm households. The results are consistent with Mendola's (2006) findings that adoption of improved agricultural technologies, such as high-yielding varieties (HYV) of rice, had a positive impact on poor farm households' incomes in Bangladesh. However, a study by Hossain *et al.* (2003) showed that adoptions of improved agricultural technologies had a negative impact on agricultural incomes of poor farm households in Bangladesh. Feder *et al.* (2006) also detected that adoption of improved agricultural technology had no significant impact on farmers' farm income in Indonesia.

It has been noted that most of these reviewed studies had evaluated the impact of adoption of improved technology by simply comparing the differences in the mean outcome of adopters and non-adopters. For instance, Haggblade *et al*. (2010) used Linear Programming approaches while others used simple Ordinary Least Squares (OLS) regression procedures. Critics observed that these approaches, such as Linear Programming approaches and simple OLS regression procedures, were flawed as they did not account for endogeneity or self-selection and non-random placement problems. Therefore, they could not identify the causal effect of the programme (Ravallion, 2002; Khandker *et al.,* 2010).

Mendola (2006) and Kassie *et al*. (2011) used Propensity Score Matching (PSM) to evaluate the impact of adoption of improved agricultural technologies on income. However, PSM only removed the observed bias, also called overt (obvious) bias (Ravallion, 2001; Lee, 2005). PSM does not remove hidden bias because of unobserved characteristics which affected farmers' self-selection into adopting a technology (Khandker *et al.,* 2010; Ravallion, 2002). Therefore, the results could have been biased. Other recent studies by Feder *et al.* (2006) and Muhammad *et al.* (2013) used the Double Difference (DD) method without PSM methods to assess the impact of improved agricultural technology adoption on income. Nevertheless, the DD method without PSM only eliminates the unobservable bias (Ravallion, 2002). DD does not remove the observable bias caused by heterogeneity in observable characteristics between adopters and non-adopters, something that could have resulted in biased conclusions about the impact of improved technology adoption on income.

None of these mentioned studies had attempted to remove both observable and unobserved bias caused by endogeneity or self-selection and non-random placement problems. Individuals that choose to participate in a programme are by definition different from those who choose not to participate. These differences, if not accounted for, may invalidate the causal comparison of outcomes of treatment status (Imbens & Woodridge, 2008). Therefore, it is noted that this study sought to correct these shortcomings by employing a version of the Double Difference (DD) approach, combined with Propensity Score Matching (PSM) methods, to evaluate the impact of the cotton YIELD Programme in Zambia. This two-pronged empirical strategy (DD approach combined with PSM) correctly estimates the impact of the programme and deals with endogeneity or self-selection and non-random placement of the programme across the communities (Khandker *et al.,* 2010). Therefore, in this study, PSM is used to obtain a matched sample of participants and non-participants so as to eliminate the observed heterogeneity in characteristics. After matching, the balancing test is also conducted using the standardised mean difference to assess the quality of matching. The standardised mean difference is important in determining whether the PSM is successful or not (Rosenbaum & Rubin, 1983). The Double Difference method is applied on the successfully matched sample of participants and non-participants of the Cotton YIELD Programme to account for the unobserved factors in order to obtain robust results.

CHAPTER 3
THEORETICAL AND CONCEPTUAL FRAMEWORKS

This chapter discusses the theory used in this study. It further discusses techniques used in previous studies, including their shortcomings. It then proceeds to indicate how the techniques selected for this study overcome the identified shortcomings.

3.1 Theoretical Framework

Since smallholder farmers in Zambia and other developing countries produce under conditions of uncertainty and market imperfections, this study adopted the expected utility maximisation framework (Ogada *et al.,* 2014). This framework considered decision making under risk and choice between risky prospects when the probabilities of the possible outcomes of that choice are objectively known. The main problem of smallholder farmers under conditions of uncertainty and market imperfections is to maximise expected utility (net revenue) subject to constraints. Assuming two production functions exist, namely one for non-participation (non-adoption of technology one) in the Cotton YIELD Programme and a second for participation (adoption of technology two) in the programme. The first and second production functions are referred to as Q_1 and Q_2. That is:

$$Q^1 = q(X1, \varepsilon 1) \qquad \text{Equation 3.1}$$

$$Q^2 = q(X2, \varepsilon 2) \qquad \text{Equation 3.2}$$

Stochastic error terms ε_1 and ε_2 capture all unobserved household heterogeneities. X_1 and X_2 are inputs necessary for technology one in Equation 3.1 and technology two in Equation 3.2, affecting outputs Q_1 and Q_2 respectively. Note that X_1 and X_2 are not equal in, for instance, content, volume and/or quality. Including prices of output (p) and inputs (r), then Equations 3.1 and 3.2 could be expanded further to express utility functions as in Equation 3.3 and Equation 3.4 below (Ogada *et al.,* 2014). That is:

$$E[U^1(\pi 1)] = E[U(pQ1(X1, \varepsilon 1) - rX1)] \qquad \text{Equation 3.3}$$

$$E[U^2(\pi 2)] = E[U(pQ2(X2, \varepsilon 2) - rX2)] \qquad \text{Equation 3.4}$$

where $E[U_1(\pi_1)]$) is the expected utility without participation, and ($E[U_2(\pi_2)]$) is the expected utility with participation. The assumption on which farmers choose between adopting a technology and not adopting is that rational farmers (consumers) usually prefer more, rather than less, utility (Hardaker *et al.,* 2004). Therefore, rational farmers would choose the risky prospect (alternative outcome) with the highest expected utility (net revenue).

Based on the expected utility maximisation framework, a smallholder farmer would participate in the Cotton YIELD Programme if the expected utility ($E[U_2(\pi_2)]$) with participation is higher than the expected utility without participation ($E[U_1(\pi_1)]$), that is, $E[U_2(\pi_2)] - E[U_1(\pi_1)]>0$ (Hardaker *et al.,* 2004). Note that the differences in the expected utility levels between participants and non-participants of the Cotton YIELD Programme are unobserved. However, the decisions to participate or not are observable. Furthermore, smallholder farmers are assumed to be heterogeneous in their characteristics such as education levels, past experience, age, marital status, gender, land ownership, access to credit and information, the market and other wealth and farm characteristics such as farm size (Kassie *et al.,* 2011; Pender & Kerr, 1998; Khandker *et al.,* 2010). The heterogeneity in characteristics of participants and non-participants might lead to self-selection into the Cotton YIELD Programme. For example, farmers with high education may be more likely to participate in the Cotton YIELD programme. In addition, the Cotton YIELD programme was not randomly placed but was placed according to the needs of the community and individuals who in return were self-selected into the programme. Self-selection could be due to observable and unobservable factors (Kassie *et al.,* 2011). Self-selection and programme placement give rise to methodological problems which needed to be addressed in this study. This is because farmers participating in the Cotton YIELD programme may not be representative of non-participants.

3.2 Conceptual Framework

Agricultural net income is defined as the sum of net income from crops and livestock (Davis *et al.,* 2012). However, crop net income will be used as a proxy for agricultural net income in this study for two reasons. Firstly, the focus of the Cotton YIELD Programme is to enhance crop net income (DZL, 2015). Secondly, livestock income contributes 45 % to overall agricultural net income in Zambia (MAL *et al.,* 2012). Therefore, inclusion of livestock income in the analysis of the Cotton YIELD Programme impact could significantly impair the results. Crop net income is defined as the net value of all crops produced by the farm household (Ng'ombe, 2013). Ravallion (2002) and Wooldridge (2013) defined impact as the differences in the expected value of the outcome variable attained by participating households and that which they would have attained had they not participated in the programme. That is:

$$E(Y) = E(Y1i - Y0i / Pi = 1) \qquad \text{Equation 3.5}$$

If the i^{th} individual participated in the Cotton YIELD Programme, their level of agricultural income would be Y1i and if they had not their agricultural income would have been Y0i. Pi is a dummy variable equal to one (1) after programme implementation and zero (0) otherwise. This impact is the conditional mean impact; conditioning on participating in the programme. It is also called treatment effect or the average effect on the treated (ATT) (Wooldridge, 2013).

However, if there is a difference in mean agricultural income between participants (Y1) and non-participants (Y0) in the absence of the programme, a bias (b) would arise and this bias could be given by:

$$b = E(Y1i|Pi = 0) - E(Y0i|Pi = 0) \qquad \text{Equation 3.6}$$

The above bias could be corrected if E(Y1i|Pi=0) was known, that is, the level of agricultural income of the participants had they not participated in the Cotton YIELD programme. However, what the level of agricultural income would have been had the participants not participated in the programme could not be observed. What could not be observed is called the counterfactual agricultural income. Had the programme been assigned randomly, the participants and non-participants could have similar income. That is, the expected agricultural income of non-participants of the Cotton YIELD programme would have correctly revealed the counterfactual.

Randomisation is not possible for the Cotton YIELD programme due to high costs. Therefore, quasi-experimental designs and statistical controls must be used to address the differences in characteristics between the participant and non-participant groups (Baker, 2000; Rubin, 1974). According to Khandker *et al.* (2010), under some form of exogeneity, the conditional average treatment effect on the treated (ATT) is estimated in most quasi-experimental impact studies as:

$$E(Y) = E\,(Y1i - Y0i|X, Pi = 1) \qquad \text{Equation 3.7}$$

The assumption of Equation 2.7 is that conditioning on carefully selected covariates (X) renders household treatment effect status independent of potential outcomes. This makes it possible to attribute any systematic differences in the agricultural net income between participants and non-participants with similar values of the covariates to the Cotton YIELD programme. A more appealing version of Equation 3.7 involved replacing X with the estimated conditional probability of participation, referred to as the propensity score. Rosenbaum and Rubin (1983) proved that conditioning on propensity score was equivalent to conditioning on X where the former was defined as:

$$p(X) = P\,(P = 1, X) \qquad \text{Equation 3.8}$$

where P is the propensity score.

To optimally balance the observed covariates between participants and non-participants, PSM was used for selecting the comparison group. Basically, PSM matches observed characteristics of participants and non-participants according to the predicted propensity of participating (Ravallion, 2002). Therefore, the Cotton YIELD programme participants were matched to non-participants based on probability of participation or propensity score. Several versions of balancing tests exist in literature (Ng'ombe, 2013). However, Rosenbaum and Rubin (1983) suggested a standardised mean difference between participants and non-participants of not greater than 20 %, as above 20 % was an indication of failure of the matching process (Ng'ombe, 2013). Furthermore, a comparison of pseudo R^2 and likelihood ratio tests obtained from probit regression analysis before and after matching were also recommended (Ng'ombe, 2013). After matching, there should be no systematic differences in the distribution of observed characteristics between the two (2) groups of the Cotton YIELD programme.

After selecting the control group using PSM, the differences in the unobserved covariates between participants and non-participants of the Cotton YIELD programme could be corrected using instrumental variable methods (Ravallion, 2001). However, Wooldridge (2013) and Kassie *et al.* (2011) argued that good instruments were hard to find and recommended a Double Difference (DD) method to correct for differences in the unobserved covariates if baseline data was available. Wooldridge (2013) proved that the impact of the unobserved covariates that affect the outcome of interest are eliminated through the DD method by subtracting the changes in agricultural net income of the Cotton YIELD programme non-participants before and after the programme from participants, as shown in Equation 3.9.

$$E(Y) = E((Y1i - Y0i|Pi = 1) - E(Y1i - Y0i|Pi = 0) \qquad \text{Equation 3.9}$$

where $(Y_{1i}\text{-}Y_{0i}|P_{i=}1)$ is the expected difference in agricultural net income of participants and non-participants in the follow-up survey (after the programme), whereas $(Y_{1i}\text{-}Y_{0i}|P_{i=}0)$ is the expected difference in agricultural net income variable of participants and non-participants in the baseline (before the programme), and E(Y) is the impact estimate also known as ATT (Wooldridge, 2013). The growth in agricultural net income of the non-participants of the Cotton YIELD programme over time, also referred to as hidden bias due to unobserved covariates, is eliminated in the process (Wooldridge, 2013; Kassie *et al.*, 2011). That is:

$$T = E(Y0i|Pi = 1 - Y0i|X, Pi = 0) \qquad \text{Equation 3.10}$$

where $(Y_{0i}|P_{i=}1)$ is the agricultural net income after the programme, $(Y_{0i}|P_{i=}0)$ is agricultural net income before the programme for non-participants, and T is the bias due to unobservable factors. In the absence of unobserved bias (T=0), agricultural net income after the programme $(Y_{0i}|P_{i=}1)$ is expected to be equal to agricultural net income before the programme $(Y_{0i}|P_{i=}1)$ for non-participants (Wooldridge, 2013). Therefore, in this study, PSM was used to account for observable heterogeneity in characteristics and DD for the unobservable factors.

CHAPTER 4
METHODS AND PROCEDURES

This chapter of the study looks at the area of the study, data collection and sampling procedure, and the analytical approaches used in this study.

4.1 Study Area

In Zambia, there are three (3) agro-ecological regions, namely regions I, IIa, IIb, and III as shown in Figure 4.1 below. Agro-ecological region I receives less than 750 millimetres of rainfall, region II between 750 and 1000 millimetres, and region III above 1000 millimetres of rainfall per year. This study was conducted in Mumbwa district of the Central province of Zambia, located in agro-ecological region IIa as indicated in Figure 4.1. The district receives between 750 and 1000 mm of rainfall per year, making it suitable for cotton production as the crop requires a warm, frost-free growing season of 150–180 days and well-distributed rainfall of 600–900 millimetres (RATES, 2003). Central province has about 22 155 cotton farmers, and of these about 9 305 are found in Mumbwa district (Tschirley & Kabwe, 2009). The district has seven shed areas manned by shed area managers and with more than 7 000 Cotton YIELD Programme farmers (DZL, 2015). Shed areas are operational areas of Dunavant Zambia Limited. The study covered all the shed areas in Mumbwa district. Mumbwa district was best suitable for this study because of the presence of the programme activities of DZL through the Cotton YIELD programme office.

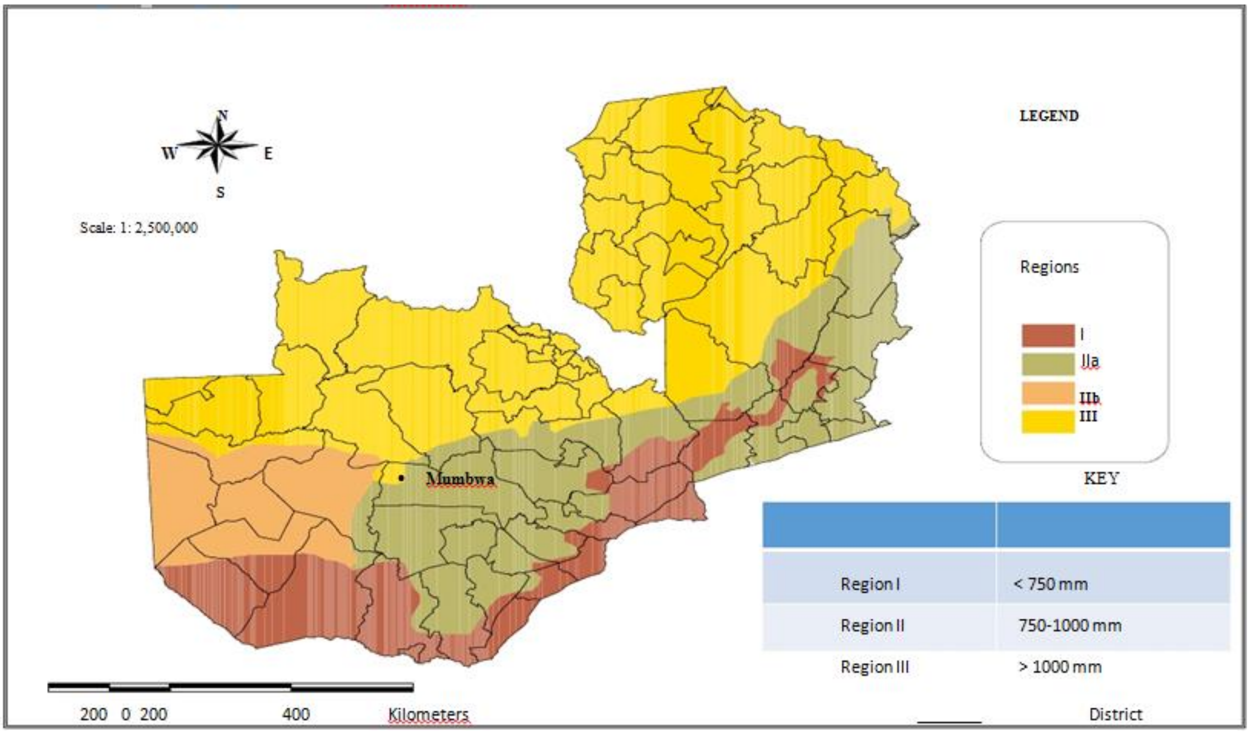

Figure METHODS AND PROCEDURES.1: Geographical Location of Mumbwa District in Zambia

4.2 Data Collection and Sampling Procedure

Both primary and secondary data were used in this study. Primary data was collected through a sampled household survey conducted in the 2015 agricultural season. Secondary data came from the baseline survey conducted by DZL in 2005 before implementing the Cotton YIELD Programme. According to Ng'ombe (2013), household size was one of the factors that affect agricultural net income. The mean household size in Zambia was about six (6) members, with variance of about 2.986 (Ng'ombe (2013). These results were consistent with the findings of CSO (2010: 27). According to Hassan (2015), the sample size (n) that generated 99 % precision (F=1 %) could be computed as follows:

Equation 4.1

$$n = \left(100 * S / F * \bar{Y}\right)^2$$

where S is the variance (2.986), F is the precision level at 1 %, and Ȳ is the mean household size (6.015). Using the above formula in Equation 4.1, the sample size (n) was 2 477.

A sample size of 2 477 farm households was not financially feasible and was larger than the sample size used in the baseline survey, while at 5 % level of precision, a sample size of 99 farm households was too small for this study. At F value of four per cent (4 %), the sample size was 150 farm households, which was the same as the sample size used in the baseline survey and was fixed as such. This sample size not only ensured precision of estimates but was also within the financial and time resource constraints required to conduct this study. The farm households were sorted into the sample units using stratified random sampling procedure. The random sampling procedure was employed in selecting observations into the sample because it was the same procedure used in the baseline and also ensured precision of results.

The stratified random sampling procedure was undertaken by first splitting the sampling frame (list of DZL cotton farmers) into Cotton YIELD Programme participants and non-participants. This procedure facilitated fitting homogeneous characteristics within the groups, hence reducing biases and estimation errors as the sample was more representative (Hassan, 2015). There were 7 000 participants of the Cotton YIELD Programme in Mumbwa district. This represented 42 % of the total cotton farmers in the district (as discussed in the study area above). According to Ravallion (2002), the total number of observations in the control group (non-participants) in the sample must be more than in the treatment group (participants) so as to avoid incomplete matching. In order to ensure complete matching, a variable sampling fraction was employed in which 63 participants (42 %) and 87 non-participants (58 %) from the follow-up survey were randomly selected from each stratum and interviewed. A total sample size in the follow-up survey was 150. However, the total sample size for this study was 300 because of the additional 150 observations obtained from the baseline conducted by DZL in 2005.

Structured questionnaires collected data from the follow-up survey as the literacy levels of the Cotton YIELD programme participants and non-participants varied. Owing to this, structured questionnaires helped to obtain accurate and reliable information. Data was collected on crop and livestock production, costs of production, demographics (age, gender, educational level, marital status and family size), wealth-related factors and farm characteristics (asset value, farm size, land cultivated, labour, ownership of animal traction and access to off-farm income), as well as on institution and access-related factors (distance to extension agents and market outlets, access to credit and membership to local farmer organisation).

4.3 Analytical Approach

The Statistical Package for Social Sciences (SPSS), Statistics and Data (STATA) and Microsoft Excel were used to generate descriptive statistics. The PSM and DD models were used to obtain quantitative estimates of the parameters in STATA. The variables used in this study are presented in Appendix 1 and were selected based on the expected utility theory as discussed in sub-section 3.3 above. The theory of expected utility assumes that a farm household, as a rational decision maker, tries to maximise expected utility (net revenue) subject to their constraints (Hardaker *et al.*, 2004). Smallholder farmers likewise make participation decisions in agricultural programmes that maximise their expected utility (net revenue) subject to their constraints. Therefore, based on the expected utility theory, the exact effect of age on participation decisions is ambiguous because younger farmers, despite having lower risk aversion behaviour, might have less farming experience (Ng'ombe, 2013). Similarly, the exact effect of family size on participation decisions is ambiguous, so its ultimate effect remains an empirical question to be answered in this study. However, gender of the household head could be linked to factors that indirectly influence participation decisions. Male-headed households have larger farm areas and better access to labour to adopt new technologies than female-headed households do (Doss & Morris, 2000). Therefore, gender is expected to be negatively associated with participation decisions if the household head is female. Marital status is expected to negatively influence participation decisions if the household head is not married. Not-married household heads are less likely to adopt new technology due to resource constraints (World Bank, 2012). Education level of the household head is expected to influence participation decisions positively and is included in the model as educated decision makers understand the benefit of technology better (Hossain & Sen, 1992; Elias *et al.*, 2013).

Similarly, variables such as labour availability, farm size and assets provide services and are resources available to the farmer in his or her farming activity (Langyintuo & Mungoma, 2008). Therefore, they are expected to increase participation decisions. However, distance to market outlets and extension agents are used as proxies for transaction costs and costs for searching for information, respectively (Nell *et al.,* 1999). Therefore, they are expected to negatively influence participation decisions. Access to credit and membership of local farmer organisation are expected to positively influence participation decisions. This is because through local farmer organisations, farmers are able to share experiences and exchange information about the programme when they meet, thereby controlling participation decisions. The exact effect of access to off-farm income on participation decisions was ambiguous and remains an empirical question. This is because those smallholder cotton farmers who earn more off-farm income spend less time on agricultural activities. However, farmers that have more off-farm income are more likely to finance their agricultural activities (Tschirley & Kabwe, 2009). A detailed summary of definitions and descriptions of variables used in the analysis, as discussed above, are presented in Appendix 1. The Probit model was used to identify factors that influence smallholder farmers' participation in the Cotton YIELD programme. According to Wooldridge (2013), the Probit model is more favourable than the logit model because the former assumes that the error term is normally distributed and that several specification problems are easily analysed. Therefore, in this study, the Probit regression of a participation dummy on a set of control variables was used to identify factors that influence participation in the Cotton YIELD programme and obtain propensity scores. The equation is given as:

$$D = \alpha_0 + \alpha_i X_i + \varepsilon_i \qquad \text{Equation 4.2}$$

where D is the programme participation dummy and equal to one if participant and zero otherwise, X_i are factors that influence participation, and ε is the error term.

The propensity scores generated were then used to match participants to non-participants of the cotton YIELD programme in STATA. Balance tests were also conducted to assess the quality of matching through a comparison of pseudo R^2 and likelihood ratio tests. It was expected that there should be no significant differences in the distribution of covariates between groups after matching. This is because impact estimates based on unmatched samples are more biased and less robust than matched samples (Ng'ombe, 2013). Since PSM optimally balances observed covariates between participants to non-participants, based on propensity scores, it is the obvious method for selecting the comparison groups in the Double Difference (DD) method. The DD method was used to account for unobserved bias due to unobserved heterogeneity in characteristics between participants and non-participants (Wooldridge, 2013; Ravallion, 2002). Failure to control for unobserved covariates could severely bias impact estimates and lead to misleading policy implications.

4.4 Data Collection Limitations

Data collection in this study was limited by financial resources and the time factor and, therefore, data could not be collected in all the three provinces where the Cotton YIELD programme was being implemented.

CHAPTER 5
RESULTS AND DISCUSSIONS

This chapter discusses the findings from statistics of the impact of the Cotton Yield Programme and factors that influence smallholder farmers' participation in the programme.

5.1 Data and Descriptive Statistics

Data used for this study was derived from two farm household surveys of cotton farmers randomly selected from Mumbwa district of the Central province of Zambia. The first data set was a baseline survey conducted by DZL in 2005, while the second dataset was a follow-up survey undertaken in 2015. The follow-up survey, focusing on the 2014/2015 cropping season, was conducted on cotton farming households in the same study area as the baseline survey so as to avoid incomplete matching (Ravallion, 2001). The study area is Mumbwa district where DZL has been implementing the Cotton YIELD Programme. At least 150 smallholder cotton farmers were selected randomly in each survey, leading to a total sample size of 300 cotton farmers for this study. Data was collected on crop revenue, household characteristics, household wealth variables, farm characteristics, institutional and access-related factors such as access to markets, credit, and extension services using a structured questionnaire. The household characteristics on which data was collected include age, gender, educational level, marital status and family size. The household wealth variables and farm characteristics included asset value, farm size, land cultivated, labour used, ownership of animal traction and access to off-farm income, while institutional and access-related variables on which data was collected included distance to extension agents, distance to markets, access to credit, and membership to a local farmer organisation. In this study, participants are classified as smallholder cotton farmers who adopted the technology of the Cotton YIELD Programme, while non-participants refer to those that did not adopt the technology of the Cotton YIELD Programme.

5.1.1 Demographic Statistics

The demographic characteristics of the farm households analysed include age, gender, education, marital status and family size. Table 5.1 below shows the results of the continuous variables of demographic characteristics analysed. These include age, years of education and family size of the cotton farm household heads who are also decision makers.

Table RESULTS AND DISCUSSIONS.1: Characteristics of Smallholder Cotton Farm Households Respondents in Zambia, 2015

Variable Description	Minimum Statistics	Maximum Statistics	Means	Standard Deviation
Demographics Characteristics				
Decision Maker' age in years	30.00	71.00	44.95	10.30
Level of education of the Decision Maker in years	0.00	13.00	7.07	3.36
Family size	1.00	12.00	5.90	2.12

Source: Author's calculations, baseline data from DZL, 2005 and follow-up survey, 2015

The age of the decision maker is important in determining whether the decision maker benefited from the experience of old age, or risk-taking attitude of young age in cotton production. The results indicate that the minimum age of the decision makers is 30 years, while the maximum is 71 years. However, the overall mean age of the decision makers sampled is 44.95 years, with a standard deviation of 10.30 years. The statistical age dispersion of the decision makers is between 34.65 and 55.25 years, suggesting that decision makers who produce cotton are middle aged. Another important variable is the education level of the decision makers which is measured by years spent in school. The average years of education of the farm decision makers are 7.07 years, with a standard deviation of 3.36 years, indicating that years of education varied between 10.43 and 3.71. The results suggest that most decision makers who grow cotton in Zambia have a basic education. Table 5.1 also shows that the minimum family size of the decision makers is one member, while the maximum is 12 members. However, the average family size is 5.9 members, with the standard deviation of 2.12 members, which is similar with the national average household size of 5 to 6 members in Zambia (CSO, 2010).

The gender of the farm household heads was also analysed and the results are reported in Figure 5.1 below. The results indicate that of the 300 farm households sampled, the majority (61 %: 183 of 300) are male headed. Working on the assumption that the sample is a true reflection of Zambia's smallholder cotton farmers, this sector is male dominated. An implication that immediately springs to mind is that male-headed households have greater access to land and labour than their female counterparts in developing countries do (World Bank, 2012). According to Tschirley and Kabwe (2009), cotton production is labour intensive and therefore farmers with greater access to labour could readily engage in cotton production.

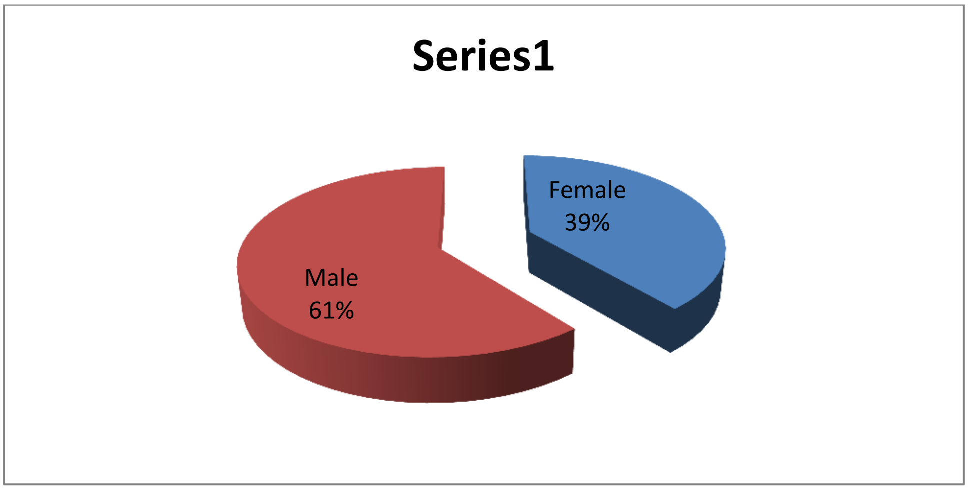

Figure
RESULTS AND DISCUSSIONS.2: Gender of Smallholder Cotton Farm household Heads Respondents in Zambia, 2015

Source: Author's calculations, baseline data from DZL, 2005 and follow-up survey, 2015

Marital status of the smallholder cotton farm households is one of the demographic characteristics that were analysed and the results are reported in Figure 5.2 below. The results show that of the 300 cotton farm household heads sampled, the percentage ratio of married to non-married is 86:14. Married farm household heads have access to more labour in Zambia, as they have larger family sizes (Ng'ombe, 2013). Hence, a higher proportion of married farm household heads is engaged in cotton production as the crop is labour intensive (Tschirley & Kabwe, 2009).

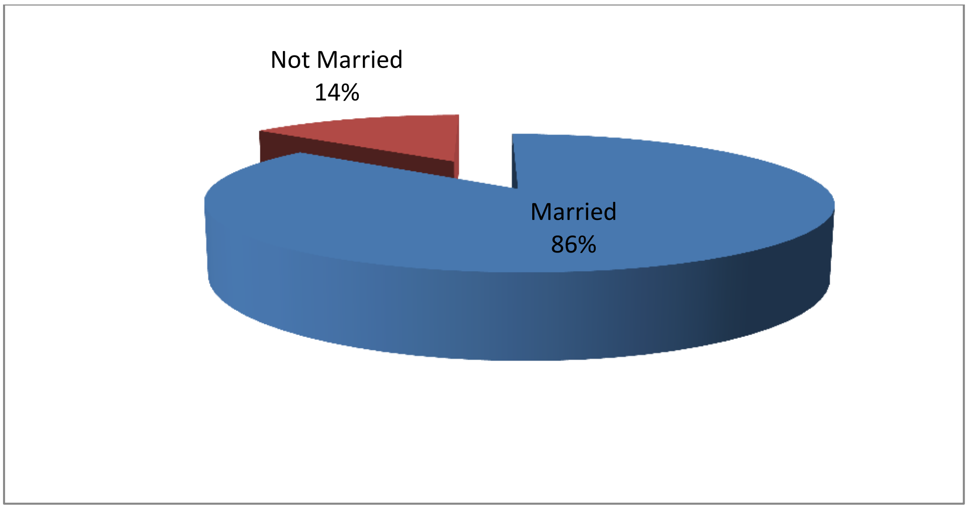

Figure
RESULTS AND DISCUSSIONS.3: Marital Status of Cotton Farm Household Heads Respondents in Zambia, 2015

Source: Author's calculations, baseline data from DZL, 2005 and follow-up survey, 2015

5.1.2 Land Ownership by Gender and Marital Status

Access to agriculture land remains a challenge in Zambia (World Bank, 2012). The results in Table 5.2 below show access to agricultural land by gender.

Table
RESULTS AND DISCUSSIONS.2: Agricultural Land Distribution of Respondents by Gender in Zambia, 2015

Gender|Farm size	Less than 2 hectares	2-5 hectares	More than 5 hectares	Total
Female numbers (%)	47 (40.2)	39 (33.3)	31 (26.5)	117(100)
Male numbers (%)	45 (24.6)	62 (33.9)	76 (41.5)	183 (100)
Total numbers (%)	92 (30.6)	101 (33.7)	107 (35.7)	300 (100)

Note that percentages (%) are in parentheses
Source: Author's calculations, baseline data from DZL, 2005 and follow-up survey, 2015

The results in Table 5.2 above indicate that 26.5 % of the total female-headed households have a farm size of more than five hectares, compared with 41.5 % for males. Overall, 35.7 % of the sampled smallholder cotton farm household heads in Zambia have a farm size of more than five hectares. Lack of access to agricultural land in Zambia, particularly by female-headed households, has been attributed to the biased process of land administration which mostly favours males (Fisher & Kandiwa, 2014). Smallholder agriculture is normally conducted on common land owned by the state, though controlled and administered by traditional leaders of a defined chiefdom (Kishindo, 2004). Smallholder farmers gain access to land through inheritance and marriages. In Zambia, various land transfer systems exist because of different descent practices, namely patrilineal and matrilineal inheritance systems. Under patrilineal inheritance system, parents allocate land to their sons while in a matrilineal inheritance system, husbands gain access to land through their wives (Kishindo, 2004). As the patrilineal system of land transfer is more common in Zambia, women cannot inherit their fathers' land. In addition, land might not be available to the woman whose husband has died, as relatives of the deceased may grab the land, resulting in less access to land for females (Place & Otsuka, 2001). Large farm sizes attract participation in agricultural programmes that promote the adoption of modern technologies. However, it is unlikely that female-headed households would participate due to their lesser access to land (World Bank, 2012). Therefore, policy interventions that empower women with land could increase smallholder female farmers' access to agricultural land.

The distribution of agricultural land by marital status was also analysed and the findings are presented in Table 5.3 below.

Table

RESULTS AND DISCUSSIONS.3: Agricultural Land Distribution of Respondents by Marital Status in Zambia, 2015

Marital Status Farm size|	Less than 2 hectares	2-5 hectares	More than 5 hectares	Total
Married Decision Makers number (%)	103 (40.1)	78 (30.4)	76 (29.6)	257 (100)
Not married Decision Makers number (%)	20 (46.5)	15 (34.9)	8 (18.6)	43 (100)
Total	123 (41.0)	93 (31)	84 (28.0)	300 (100)

Note that percentages (%) are in parentheses

Source: Author's calculations, baseline data from DZL, 2005 and follow-up survey, 2015

The findings show that 18.6 % of the unmarried household heads have farm sizes of more than five hectares, compared with 29.6 % for the married household heads. The results for Zambia's smallholder respondents in Table 5.3 correspond with Fisher and Kandiwa's (2013) observations in Malawi that married farm household heads had more access to agricultural land than unmarried household heads did. Parents gave agricultural land to children for farming once married, hence they have more access to agricultural land (Fisher & Kandiwa, 2014). Although a larger farm size accelerates adoption of new technologies, it may not be possible to curtail further sub-division of agricultural land as population increases. Therefore, expanding the industrial sector to absorb more people from the agricultural sector so as to reduce pressure on agricultural land could be a policy option. In addition, other policy options, such as land rental markets, could also increase farmers' access to agricultural land and this could be achievable through land banks.

5.1.3 Membership of Farmer Organisation and Access to Credit

Institutional- and access-related factors analysed include relationship between membership of local farmer organisations and access to credit. Membership of a local farm organisation is vital for gaining access to information and other services (Beaman & Dillon, 2014).

Table RESULTS AND DISCUSSIONS.4: Respondents' Membership to Local Farmer Organisations and Access to Credit in Zambia, 2015

Membership/Access to Credit|	No Access to Credit	Access to Credit	Total
Member numbers (%)	128 (70.3)	54 (29.7)	182 (60.67)[1]
Not Member numbers (%)	108 (91.5)	10 (8.5)	118 (39.33)[1]
Total Observations numbers (%)	236 (78.7)	64 (21.3)	300 (100)

Note that percentages (%) are in parentheses. 1: % of 300 respondents

Source: Author's calculations, baseline data from DZL, 2005 and follow-up survey, 2015

The results in Table 5.4 above show that of the 300 smallholder cotton farmers sampled in Zambia, 60.67 % are members of co-operatives, whereas 39.33 % are not. In addition, 29.7 % of those that belong to co-operatives have access to credit, compared with 8.5 % for those that do not belong to any co-operative. Although the results suggest that membership of a farmer organisation increases access to credit, access to credit is still relatively low, at 21.3 % of the total farm households sampled. Most smallholder farmers may not acquire credit through commercial banks due to lack of collateral and the risky nature of their farming businesses (Ogada *et al.*, 2014). Therefore, mobilising smallholder farmers to form co-operatives through which to pool resources might accelerate access to credit.

5.2 Descriptive Characteristics of Participants and Non-participants

Statistical significance tests and summary statistics on equality of proportions for binary variables and equality of means for continuous variables for participants and non-participants are reported in Table 5.5 below. Some of these selected variables (to be named later) were also used as independent variables in the estimate models to be presented later and were selected on the basis of theoretical discussions. This study analysed a dataset of 300 smallholder cotton farmers; of these, 42 % are Cotton YIELD Programme participants, while 58 % are non-participants, as shown in Table 5.5 below.

Table

RESULTS AND DISCUSSIONS.5: Descriptive Characteristics of Participants and Non-participants of Cotton YIELD Programme in Zambia, 2015

Variable Description	Mean Participants	Mean Non-participants	Difference
Number of observations (300)	126	174	
Demographic Characteristics			
Decision Makers' age in years	44.44	45.46	-1.02
Gender of the Decision Maker (1=male, 0=otherwise)	0.57	0.64	-0.07
Level of education of the Decision Maker in years	7.75.	6.39	1.36**
Marital status of the Decision Maker (1=single, 0=otherwise)	0.08	0.19	-0.11***
Family size	5.80	6.02	-0.22
Household wealth variables and farm characteristics			
Farm size (ha)	4.75	3.09	1.66***
Land cultivated (ha)	1.65	1.51	0.14
Active family labour (Adult equivalents)	5.06	3.91	1.15***
Own animal traction (1=yes, 0=otherwise)	0.59	0.30	0.29***
Access to off-farm income (1=yes, 0=otherwise)	0.40	0.59	-0.19
Own radio or television set or mobile phone	0.35	0.19	0.16**
Assets value (ZMK00)	7.44	5.48	1.96***
Institutional and access-related factors			
Distance to local markets outlets (km)	8.56	10.97	-2.41***
Distance to extension agents (km)	5.33	7.78	-2.45***
Access to credit (1=yes, 0=otherwise)	0.39	0.08	0.31***
Membership to farmer organisation (1=yes, 0=otherwise)	0.87	0.42	0.45***

* Statistically significant at 10 %, ** at 5 % and *** at 1 %.

Source: Author's calculations, baseline data from DZL, 2005 and follow-up survey, 2015

5.2.1 Demographic Characteristics of Participants and Non-participants

The results in Table 5.5 above show that demographic characteristics of participants and non-participants differ significantly. Average years of education for participants are 7.75 years, and 6.39 years for non-participants and the difference is statistically significant at 5 on common land, suggesting years of education might positively influence participation decisions in the programme. The results resonate with Rubas' (2004) findings that farmers with more years of education understood the benefit of technologies much better and were more likely to adopt new technologies. The results also indicate that the highest proportions of non-participants, compared with participants, are single and the difference is statistically significant at 5 %. The results suggest that not being married might influence participation decisions in the Cotton YIELD Programme negatively. Unmarried household heads have less access to labour and therefore are less likely to adopt new technologies (World Bank, 2012).

5.2.2 Wealth and Farm Characteristics of Participants and Non-participants

Participants and non-participants are distinguishable in terms of their wealth and farm characteristics. The difference between the two groups' average farm size, asset value and active family labour are statistically significant. On average, participants have larger farm sizes of 4.75 hectares, whereas non-participants have 3.09 hectares. It thus seems as if farm size is a determinant in a decision maker's choice to participate in the programme. The results support the observations by Darr and Chern (2000) that adopters of improved technologies had larger farm sizes than non-adopters do. Participants are progressive farmers (risk seekers) that have greater access to private land and might utilise resources more efficiently if their demographics are right, hence they are more likely to adopt new technologies (Langyintuo & Mungoma, 2008).

Similarly, participants have greater asset values and numbers of farm workers (labour) than non-participants do. The average active, family labour for participants is 5 adult equivalents, compared with 4 adult equivalents for non-participants. In addition, 59 % of the participants own animal traction, compared with 30 % for non-participants, and the difference is statistically significant, suggesting that participants are progressive farmers with greater wealth. Wealthier farmers have higher risk-bearing ability, hence are more likely to adopt new technologies (Kassie *et al*., 2011). A significantly higher proportion of participants owns either a radio or television set or mobile phone, compared with non-participants. Ownership of radios, television sets and mobile phones is critical for farmers' access to information (Asfaw & Shiferaw, 2010). Therefore, possession of a media instrument may have a positive effect on participation decision in the Cotton YIELD Programme.

5.2.3 Institutional- and Access-Related Factors of Participants and Non-participants

Institutional- and access-related factors analysed in Table 5.5 above varied significantly between participants and non-participant of the Cotton YIELD Programme. A significantly higher proportion of participants (39 %) has access to credit, compared with 8 % for non-participants, suggesting that access to credit is positively associated with participation decisions. The results are in agreement with Gerhart's (1975) observations in Kenya that access to credit encouraged adoption of new technologies. Similarly, participants are nearer to extension agents and market outlets than non-participants are and the difference is statistically significant. Proximity to extension services and markets influences the participants positively in accepting the Cotton YIELD Programme. Other than accessing information about the programme through extension agents and media, farmers also access information through local farmer organisations. Membership of a local farmer organisation facilitates informal exchange of information among farmers. The results also show that a significantly high proportion of participants (87 %) are members of local farmer organisations, against 42 % for non-participates. The results correspond with Beaman and Dillon's (2014) findings that social networks through cooperatives increased the uptake of improved technologies and were, therefore, critical in the diffusion of new technologies among farmers.

5.2.4 Outcome variables

The outcome variable analysed is agricultural net income, also referred to as net farm income. The results from the analysis of the observed outcome variable are reported in Table 5.6 according to participation status.

Table

RESULTS AND DISCUSSIONS.6: Respondents' Net Farm Income by Participation Status in Zambia, 2015.

Variable Description	Mean Participants	Mean Non-participants	Difference
Number of observations (300)	126	174	
Outcome Variables			
Agricultural net income (ZMK)/ha	1, 813.40	806.39	1, 007.01***

* Statistically significant at 10 %, ** at 5 % and *** at 1 %.
Source: Author's calculations, baseline data from DZL, 2005 and follow-up survey, 2015

The results show significant differences in average agricultural net income between participants and non-participants of the programme. On average, participants of the Cotton YIELD Programme achieve higher profits from crop production than non-participants do. Average agricultural net income for participants is ZMK1,813.40, compared with ZMK806.39 for non-participants. The results are consistent with Haggblade *et al*. (2011), Nyanga *et al*. (2011) and Fisher and Kandiwa's (2013) findings. Haggblade *et al*. (2010) compared observed mean farm net income of adopters and non-adopters of improved agricultural technologies in Zambia. The study found that adopters had achieved higher observed mean farm net income than non-adopters had. Similarly, Nyanga *et al.* (2011) also established that adoption of modern technologies had a positive impact on farm household incomes.

It is evident from the results of the summary statistics and statistical significance tests reported in, and discussed based on, Table 5.5 above that participants and non-participants differ significantly. The heterogeneity in observable characteristics between the two groups may be attributable to endogeneity or self-selection. Endogeneity or self-selection, if not accounted for, could lead to biased conclusions about the impact of the Cotton YIELD Programme on agricultural net income (Ravallion, 2001; Asfaw and Shiferaw, 2010; Heckman, 1979). Therefore, the findings in Table 5.5 motivated this study to use Propensity Score Matching (PSM) to control for heterogeneity in observable characteristics so as to obtain robust results. PSM removes heterogeneity by balancing the observed covariates between the comparison (non-participant) group and treatment (participant) group (Ravallion, 2001; Heckman, 1979).[3] Therefore, it is the obvious method of selecting the comparison group in in Double Difference studies.

3 Propensity Score Matching (PSM) controls for self-selection by creating the counterfactual for the group of participants (Heckman *et al.,* 1998). PSM constructs a statistical comparison group by matching every individual observation on participants with individual observation from the group of non-participants with

similar characteristics. The matching process creates an experimental dataset that is conditional on observed characteristics; the selection process is random (Khandker, 2010). For more explanation of the PSM, see Rosenbaum and Rubin, (1983); Heckman *et al.,* (1998).

CHAPTER 6
FINDINGS AND DISCUSSION

This section discusses the results from the Probit and Double Difference Models in line with the objectives; that is, to determine the impact of the Cotton Yield Programme and factors that influence smallholder farmers' participation in the programme. The chapter also discusses the factors that affect the impact of participating in the Cotton Yield Programme.

6.1 Econometric Analysis of the Cotton YIELD Programme's Impact

Although the summary statistics and tests reflected in Table 5.6 above suggest that the Cotton YIELD Programme might have a positive impact on the overall agricultural net income, the results are only based on observed mean differences in the agricultural net income of participants and non-participants. These results may not be solely attributable to participating in the Cotton YIELD Programme, as there are other factors – both observable and unobservable – that might affect the programme's impact. In order to correctly measure the impact of the Cotton YIELD Programme, it is imperative to take into account both observable and unobservable heterogeneity in characteristics between the two groups in this study (Ravallion, 2001; Davis *et al.,* 2012).

The estimation of the Cotton YIELD Programme's impact on agricultural income is one of the specific objectives of this study. Firstly, PSM was applied to the raw data sets to match participants to non-participants so as to control for observable heterogeneity in characteristics between the two groups in the sample. PSM was then followed by a Double Difference (DD)[4] method to account for unobservable characteristics, also referred to as hidden bias between participants and non-participants as discussed previously in Chapter 3. A broad set of explanatory variables were included in both the DD and PSM models.[5] These explanatory variables were selected on the basis that they affect both participation decisions and agricultural income (Kassie *et al.,* 2011). This is because the inclusion of variables that are

4 Double Difference (DD) or Difference-in: a difference method entails comparing a treatment group and comparison group before and after the intervention (Ravallion, 2001). A Double Difference method compares treatment and comparison groups in terms of outcome changes over time, relative to outcome observed for a pre-intervention baseline (Ravallion, 2001).

5 For more information about DD approach combined with PSM methods, see Khandker et al., (2010).

strongly related with the treatment variable, but weakly or not related to the outcome variable, might increase the bias (Brookhart *et al.,* 2006). The outcome variable is agricultural net income, as defined and discussed previously in section 3.2 of Chapter 3.

6.2 Estimation of Propensity Scores

One of the specific objectives of this study is to identify the factors that influence smallholder cotton farmers' participation in the Cotton YIELD Programme. In order to achieve this objective, the Probit model was used. The dependent variable used in the Probit model is a participation dummy variable which takes on the value of one (1) if a respondent is a participant, and zero otherwise. The propensity scores, also known as the probability of participation in the programme, are estimated using the Probit model. Additional information is provided by analysing the marginal effects, also known as elasticities, which are partial first-order derivatives of the probability function, evaluated at the sample means (Green, 1990). The results from the estimated Probit model are reported in Table 6.1 below and discussed before matching participants to non-participants.

The results in Table 6.1 below show that log likelihood and pseudo R^2 are -114.99096 and 0.436, respectively. The model is statistically significant with a 99 % surety (Pro>chi^2= 0.000), indicating that explanatory variables collectively explained the variation in participation decisions in the Cotton YIELD Programme. The results also show that most coefficients of the independent variables that were hypothesised to influence participation decisions have the expected signs, as discussed previously in Chapter 4 above.

Table

FINDINGS AND DISCUSSION.7: Probit Estimates of respondents' Probability of Participation in YIELD in Zambia, 2015

Dependent Variable	Probability of Participation	Marginal Effects
Participation (1=participant, 0=otherwise)	1/0	
Independent Variables		
Demographics characteristics		
Age of the of the decision maker (years)	-0.009 (0.0095178)	-0.002
Gender of the decision maker (1=male, 0=otherwise)	-0.202 (0.1989934)	-0.044
Education level of the decision maker (years)	0.337 (0.16625)**	0.007
Marital status of the decision maker (1=single, 0=otherwise)	-0.643 (0.3225745)**	-0.140
Family size	-0.079 (0.460192)	-0.017
Wealth and farm characteristics		
Land cultivated (ha)	0.061 (0.1461396)	0.014
Farm size (ha)	0.120 (0.039456)***	0.026
Active family labour (Adult equivalents)	0.205 (0.0607265)***	0.045
Own animal traction (1=yes, 0=otherwise)	0.807 (0.2139041)**	0.175
Off-farm income (1=yes, 0=otherwise)	-0.0295 (0.02125328)	-0.064
Assets value (ZMK00)	0.016 (0.0068978)**	0.003
Institutional and access-related factors		
Distance to local markets (km)	-0.111 (0.0428288)***	-0.024
Distance to extension agents (km)	-0.311 (0.891986)***	-0.068
Access to credit (1=yes, 0=otherwise)	0.725 (0.2398819)***	0.154
Membership to farmer organisation (1=yes, 0=otherwise)	0.864 (0.201167)****	0.188
Constant	-0.519 (0.6676895)	
Number of observations	300	
Log likelihood	-114.99096	
LR Chi^2 (15)	92.4	
Pro>chi^2	0.000	
Pseudo R^2	0.436	

* Statistically significant at 10 %, ** at 5 % and *** at 1 %. Note standard errors are in parentheses

Source: Author's calculations, baseline data from DZL, 2005 and follow-up survey, 2015

6.2.1 Demographic Factors

The findings on demographic characteristics from the Probit model (in Table 6.1 above) are similar to results on demographics characteristics, previously discussed based on Table 5.5 above. The results in Table 6.1 indicate that years of education and marital status are important determinants of the decision makers' choice to participate in the programme. However, age, gender and family size of the decision maker are not important. The amount of years of education has a positive coefficient and is statistically significant at 5 %, suggesting education positively influences smallholder cotton farmers' participation in the Cotton YIELD Programme. The results are consistent with the findings by Rubas (2004), Elias *et al.* (2013), and Barret *et al* (2004) that years spent on education positively influence the adoption of new technology. Farmers with more years of education have a stronger ability to decode information and analyse the importance of the Cotton YIELD Programme. The results indicate that unmarried household heads are 14 % less likely to participate in the programme than married household heads are, *ceteris paribus*. Based on Table 5.3 above, not married household heads have smaller farm sizes than married respondents do, hence they are less likely to participate in the programme. The results are consistent with the findings by Peterman *et al.* (2010) that not married household heads have less land to farm on and labour, and therefore are less likely to adopt new technologies.

Adoption literature reviewed in Chapter 2 shows that age affects adoption decision. However, the exact effect of age on adoption decisions cannot be pre-determined because older farmers are considered risk-averse and therefore are less likely to adopt modern technologies than younger farmers are. On the other hand, the literature considers older farmers as being experienced and therefore in a better position to make sound judgments regarding the adoption of new technologies, suggesting that older farmers will be quicker to adopt new technologies that offer better returns than younger and inexperienced farmers will be (Ng'ombe, 2013). The results in Table 6.1 above show that age has no significant influence on participation decision in the Cotton YIELD Programme, which is consistent with the findings by Awotide *et al.* (2012) in Nigeria. Awotide *et al.* (2012) found that participants and non-participants were similar in terms of average age, hence age had no influence on adoption decisions of a package of technologies. It is, however, still a question as to what the results would be if a sample were stratified according to age. The findings that family size has no influence on adoption decisions, although surprising, could be because some cotton farm households comprise members below the age of 15 years, who by child labour laws are not allowed to work on the farms (ILO, 2015).

6.2.2 Wealth and Asset Ownership

Wealth and farm characteristics variables were also included in the analysis. The results in Table 6.1 above show that farm size of the respondents is positively correlated with participation and statistically significant at 1 %, suggesting that farm size is a determinant of farmers' choice to participate in the Cotton YIELD Programme. An additional hectare of farm size increases the chances of participating in the Cotton YIELD Programme by 2.6 %, c*eteris paribus*. These results resonate with the observations by Darr and Chern (2000) that adoption of improved technologies was higher among farmers with more agricultural land. Therefore, policy prioritising the increasing of access to agricultural land might enhance participation in the Cotton YIELD Programme. Similarly, the number of farm workers (labour) is positively associated with participation in the Cotton YIELD Programme and statistically significantly at 1 %, suggesting that the availability of farm labour positively influences participation decisions in the programme. An additional farm worker increases a farmer's chances of participating in the Cotton YIELD Programme by 4 %, *ceteris paribus*. These results support the importance of labour in the adoption of new technology (Mendola, 2006).

Ownership of animal traction is statistically significant at 5 % and positively associated with participation in the programme. Ownership of animal traction by the respondents increases the probability of participation in the programme. Respondents who own animal traction are 17.5 % more likely to participate in the programme compared with their counterparts, holding other factors constant. Farmers who own animal traction or have more wealth are considered as progressive farmers with higher risk-bearing abilities; hence they are more likely to participate in the programme (Langyintuo & Mungoma, 2008). Therefore, policy interventions that encourage farmers to own animal traction might facilitate participation in the Cotton YIELD Programme. Similarly, assets value is statistically significantly at 5 %, is positively associated with participation decisions, and can increase the probability of participation in the programme. These findings are consistent with recent studies by Kassie *et* *al.* (2011) who reported that successful farmers have higher asset values and animal traction, hence more willing to adopt new technology. From an extension point of view, concentrating on wealthier smallholder cotton farmers who are non or potentially late adopters of technology can speed up the adoption process.

6.2.3 Access to Information

A number of institutional- and access-related factors were included in the analysis to identify factors that influence smallholder farmers' participation in the Cotton YIELD Programme. Membership of local farmer organisations is used as a proxy for access to information. Membership is positively associated with participation in the Cotton YIELD Programme and statistically significant at 1 %, suggesting that membership of local farmer organisations influences participation in the programme. Farmers that are members of local farmer organisations are 18.8 % more likely to participate in the Cotton YIELD Programme than their counterparts are, holding other factors constant. These results support the findings by Davis (2008), Marra *et al*. (2004) and Kassie *et al.* (2011) that membership of local institutions increases the probability of adoption of new technologies. Time lags do exist in adoption of new technology, as farmers tend to postpone decisions on technology adoption until his or her neighbour has tried it and demonstrated success or not. Therefore, through social networking in local farmer organisations, farmers are able to share experiences and exchange information about the programme (Marra *et al.*, 2004; Beaman & Dillon, 2014), as previously discussed in Chapter 2.

6.2.4 Access to Markets and Extension Services

Distances to market outlets and extension agents were used as proxies for transaction costs and costs of searching for information, respectively. An increase in distance to extension agents by a kilometre decreases the probability of participating in the Cotton YIELD Programme by 6.8 %, holding other factors constant. Similarly, an increase in distance to market outlets by a kilometre decreases the chances of participating in the Cotton YIELD Programme by 2.4 %, c*eteris paribus*. Smallholder cotton farmers who are nearer to extension workers have a higher chance of being assisted when a problem emerges with a new technology and are more likely to participate in the Cotton YIELD Programme (Nell *el al.,* 1999). Therefore, policy interventions, such as improved road systems that bring extension agents and markets both closer to smallholder cotton farmers, might facilitate their participation in the Cotton YIELD Programme. Access to credit is positively associated with participation and statistically significantly at 1 %. Farmers with access to credit are 15.7 % more likely to participate in the Cotton YIELD Programme than their counterparts are. Improved access to credit via, for instance, policy interventions, is a key ingredient in the adoption of new technologies. According to Gerhart (1975) and Ogada *et al.* (2014), credit enables farmers to more successfully produce higher value crops or cash crops with the help of improved technologies.

6.3 Propensity Score Matching

The results of the Probit model used to estimate the individual propensity scores[6] for the participant (treated) and non-participant (untreated) respondents are reported in Table 6.1 above. According to Khandker *et al.* (2010), a matching procedure is only performed in the region of common support as observations that fall within this region have similar observable characteristics. The results were visually inspected to capture the region of common support. This enabled the construction of a propensity score graph of the results (plotted in Figure 6.1 below). The co-ordinates of the propensity scores (X-axis) and the densities of the scores (Y-axis)[7] indicate density distribution of propensity scores, and a region of common support is seen where the two groups overlap. The density distribution of the propensity scores for the two groups of respondents shows that the common support condition is satisfied as there is considerable overlap in the distribution of the propensity scores for both participants and non-participants.

The bottom half of Figure 6.1 below shows the distribution of propensity scores for non-participants, while the upper half shows those for the participants. The common support condition is found to be in the region of [0.0088291, 0.998076][8] with 274 respondents falling within it. However, 26 observations could not satisfy the common support condition and were, therefore, dropped so as to obtain robust results. Figure 6.1 only shows observations that fell within the region of common support. A balancing test was also conducted to assess the quality of matching, and the results are reported in Appendix 2. The null hypothesis is that covariates collectively explain variations in the PSM model. However, the results

6 The probability to participate or not in the programme.

7 Densities of the scores is defined as the extent of coverage of the scores (Kassie *et al*., 2011).

8 The pscore command of STATA was used to estimate the region of common support. For details, see Khandker *et al.* (2010).

indicate that the null hypothesis supporting joint significance of covariates in the PSM model is rejected at 1 %, as indicated by the p-value. The rejection of the null hypothesis indicates that the balancing test is satisfied and the propensity score is correctly specified. The distribution of the observable characteristics of participants and non-participants of the Cotton YIELD Programme is successful. Therefore, there were no significance differences in the observable characteristics between Cotton YIELD Programme participants and non-participants that fell within the region of common support, shown in Figure 6.1 below.

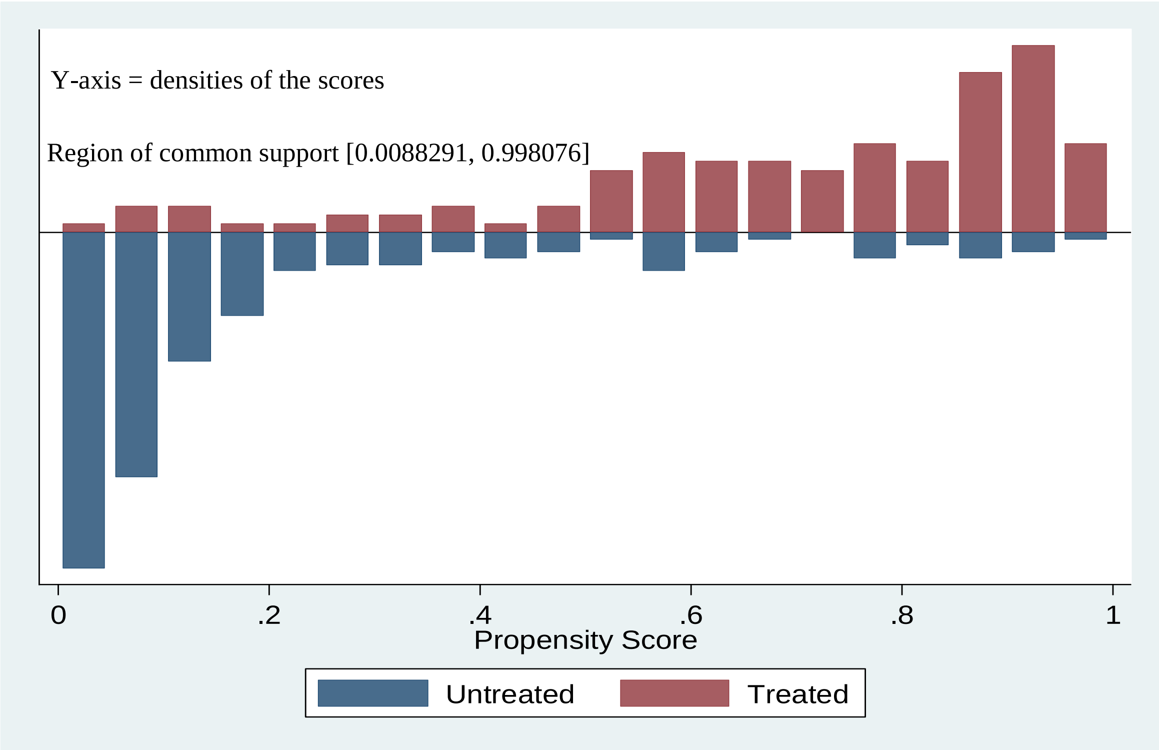

Figure
FINDINGS AND DISCUSSION.4: Propensity Score Distribution and Common Support for Propensity Score Estimates in Zambia, 2015

Source: Author's calculations, baseline data from DZL, 2005 and follow-up survey, 2015

6.4 Impact estimation using Double Difference Method

After matching participants to non-participants using PSM, the Double Difference (DD) model was then used to estimate the impact[9] of the Cotton YIELD programme on agricultural

9 The term impact is used interchangeably with average treatment effect on the treated in this paper.

net income. The results from the estimated DD model are reported in Table 6.2 below. The dependent variable used in the DD model was log crop income per hectare and independent variables included were participation dummy (p2014), year dummy (year) and a product of participation and year dummies (p2014*year) among others. Log crop income was used to measure agricultural income as opposed to crop income for easy interpretation of results (Wooldridge, 2013).

Table

FINDINGS AND DISCUSSION.8: Double Difference Estimates of Programme Impact on Agricultural Net Income in Zambia, 2015

Variable:	Coefficients
Dependent variable	
Log Crop Income per hectare[10]	
Independent Variables	
P2014 (1=participant and 0= Otherwise)	-0.027 (0.0963489)
Year (1=follow-up and 0=Otherwise)	0.023 (0.0928519)
P2014*year (impact estimate)	0.381 (0.1550724)***
Age Decision Maker (years)	-0.001 (0.0029741)
Gender (1=male, 0=otherwise)	0.029 (0.067113)
Education level of the Decision Maker (years)	0.050 (0.0096954)***
Marital status of the Decision Maker (1=single, 0=otherwise)	-0.107 (0.0644638)*
Family size	-0.013 (0.0153698)
Labour (Adult equivalents)	0.029 (0.00231761)***
Land cultivated	0.021 (0.045194)
Farm size (hectares)	0.028 (0.012587)**
Own animal traction (1=yes, 0=otherwise)	0.216 (0.0797741)***
Access to off-farm income (1=yes, 0=otherwise)	-0.095 (0.677216)
Log Assets value in ZMK	0.093 (0.035231)***
Distance to local markets (km)	-0.065 (0.078534)**
Distance to extension agents (km)	-0.330 (0.0362528)***
Access to loans/credit (1=yes, 0=otherwise)	0.083 (0.097348)
Membership to farmer organisation (1=yes, 0=otherwise)	0.173 (0.0676473)**
Constant	0.227 (0.2157488)
Number of observations	258
F (18, 239)	9.3

10 Crop net income is used as a proxy for agricultural net income in this study. The Log of crop net income per hectare is used as an outcome variable throughout the paper.

Prob > F	0.000
R-squared	0.4768**

* Statistically significant at 10 %, ** at 5 % and *** at 1 %. Note standard errors are in parentheses
Source: Author's calculations, baseline data from DZL, 2005 and follow-up survey, 2015

The results show that the R^2 is 0.4768 and THAT the model is statistically significant at 1 %, suggesting that explanatory variables collectively explained the variation in agricultural net income per hectare. The number of observations, however, dropped from the matched sample of 274 to 258, as 16 observations had zero or less than zero agricultural net income per hectare. The results in Table 6.2 above show that the mean agricultural net income per hectare for participants (represented by coefficients of p2014 + constant) and non-participants (represented by coefficient of a constant) in the baseline (before the programme) are 20 and 22.7 %, respectively. The difference in mean agricultural net income per hectare between the two groups in the baseline is insignificant at 10 %, as represented by the coefficient of participation dummy (p2014), suggesting that observable (overt) bias might have been removed by PSM methods (Mendola, 2006). However, if DD methods were to be employed in the analysis in the presence of observable bias, the results could have been biased (Ravallion, 2001).

In the follow-up survey (after initialising the programme), the mean agricultural net income per hectare for participants is 60.6 % (represented by coefficients of p2014 + year + p2014*year + constant) and 25 % for non-participants as represented by coefficients of (year + constant). The difference in mean income is statistically significant at 1 %, suggesting both participants and non-participants would have realised more income had both decided to participate in the Cotton YIELD Programme than they would have if they had not participated. The mean income of non-participants has increased from 22.7 % in the baseline to 25 % in the follow-up survey, representing a 2.3 % increment. This proves the existence of unobserved heterogeneity, also referred to as hidden bias (Davis *et al.*, 2012; Khandker *et al.*, 2010; Ravallion, 2002). However, if simple Ordinary Least Squares (OLS) regressions and PSM methods were used, unobservable bias could not have been removed (Ravallion, 2001). The unobservable bias could have resulted in biased conclusions about the Cotton YIELD Programme's impact on agricultural income (Ravallion, 2001).

6.4.1 Impact of the Cotton Yield Programme

A comparison of the Cotton YIELD programme participants and non-participants (Table 6.2 above) shows that the Cotton YIELD programme has significantly increased agricultural net income per hectare of participants by 38.1 %, as represented by the coefficient of p2014*year. The positive and significant impact of the Cotton YIELD Programme on smallholder cotton farmers' agriculture net income is consistent with the perceived role of improved technologies in reducing rural poverty via increased farm household income. The results are also consistent with recent studies by Davis *et al.* (2012), Asfaw *et al*. (2006) and Janaiah *et al.* (2006) on the effects of new technology on farm household incomes. These studies showed that adoption of new technology had a positive effect on the farm household incomes. Davis *et al.* (2012) in East Africa, using DD method combined with PSM methods, revealed that participating in agricultural programmes promoting new technology had a positive and significant effect on agricultural incomes. Asfaw and Shiferaw (2010), using endogenous switching regression combined with PSM methods, also showed that the adoption of new technology had a positive and significant impact on crop income in East Africa.

6.4.2 Factors Affecting the Cotton Yield Programme

Results in Table 6.2 above also show that the impact of participating in the Cotton YIELD Programme significantly increases with an increase in years of education level, farm size, ownership of animal traction, labour, membership to local farmer organisation and asset value. Nevertheless and as expected, it decreases with marital status, and distances to market outlets and to extension agents. An increase in the level of education by one year leads to an increase in agricultural net income per hectare by 5 %, *ceteris paribus.* The results suggest that farmers with more years of education might benefit more from the Cotton YIELD Programme. Therefore, providing basic education to farmers might enhance agricultural net income of cotton farmers, contrary to the observations by Tschirley and Kabwe (2009) in Zambia, as discussed previously in Chapter 5. They found that education had no significant effect on agricultural net income.

The results in Table 6.2 above further show that farm size is important in determining agricultural net income. An additional hectare in farm size might lead to an increase in agricultural net income per hectare of 2.8 %, *ceteris paribus,* suggesting that farmers with larger farm sizes might benefit more from the Cotton YIELD Programme. Therefore, policy measures that enable land-constrained cotton farmers to acquire additional land might increase agricultural net income. Similarly, farmers who own animal traction might gain 21.6 % more agricultural net income per hectare than their counterparts do, *ceteris paribus*, suggesting that farmers who own animal traction might benefit more from the Cotton YIELD Programme. An increase in labour by one adult equivalent is also associated with a 2.9 % increase in agricultural net income per hectare holding, other factors being constant.

Similarly, cotton farmers that belong to local farmer organisations earn 17.3 % more agricultural net income per hectare than their counterparts do, *ceteris paribus*. Membership of local farmer organisations enables farmers to not only access information about new technologies, but also other services such as credit (Ogada *et al.*, 2014). Therefore, policy interventions that encourage cotton farmers to form or join co-operatives and other local farmer institutions could enhance their agricultural net income. The results in Table 6.2 above also suggest that farmers that have higher asset values might benefit more from Cotton YIELD Programme than those who do not, hence encouraging farmers to acquire more farm assets might increase their agricultural net income. On the other hand, marital status is observed to be negatively associated with agricultural net income per hectare and is statistically significant, suggesting that not married farm household heads benefit less from the Cotton YIELD Programme. Not married farm household heads have 10.7 % lower agricultural net income per hectare compared with married farm household heads, holding other factors constant. This could be because not married household heads have less labour (Ng'ombe, 2013), as labour is critical to adoption of new technologies. An increase in distance to market outlets and extension agents by a kilometre might reduce agricultural net income per hectare by 6.5 and 33 %, respectively, holding other factors constant. Distances to market outlets and extension agents represent transaction costs and costs of searching for information, respectively, which reduces the profitability of new technologies (Nell *et al.*, 1999). Therefore, policy interventions that bring market outlets and extension agents closer to farmers might decrease the costs and enhance the agricultural net income of cotton farmers.

CHAPTER 7
CONCLUSION AND RECOMMENDATIONS

This chapter summarises the findings of the study and discusses recommendations based on the findings. The chapter also highlights areas for future research.

7.1 Conclusion

The overall aim of this study was to evaluate the economic impact of the Cotton Yield Programme on the agricultural income of smallholder cotton farmers in Zambia. In order to achieve this goal, the study used baseline data collected by Dunavant Zambia Limited in 2005 and data from a follow-up survey conducted in 2015 for the 2014/2015 farming season. To estimate the average treatment effect on the treated, the study used PSM methods to account for the observable heterogeneity in characteristics between participants and non-participants of the Cotton YIELD Programme. The PSM methods matched participants to non-participants of the Cotton YIELD Programme, based on similarity in the distribution of observable characteristics. The PSM methods were then followed by the DD method so as to account for the unobservable factors that might influence agricultural net income and participation decisions.

7.1.1 Hypotheses

Two null and two alternative hypotheses were posed in this study:

a) The null hypothesis is that socio-economic and demographic factors do not influence smallholder farmers' participation in the Cotton YIELD Programme. The alternative hypothesis is that the socio-economic and demographic factors do influence smallholder farmers' participation in the Cotton YIELD Programme.
b) The null hypothesis is that the Cotton YIELD Programme has not increased the agricultural net income of the smallholder cotton farmers. The alternative hypothesis is that the Cotton YIELD Programme has increased the net income of the smallholder cotton farmers.

The overall conclusion of this study is that years of education, farm size, membership of local farmer organisations, assets value, access to credit, and ownership of animal traction positively influence smallholder cotton farmers' participation in the Cotton YIELD

Programme. However, distances to extension agents and market outlets negatively influence smallholder farmers' participation.

It is evident from the results that the (a) null hypothesis, that demographics and socio-economic factors do not influence participation in the Cotton YIELD Programme, is statistically not significant and cannot be accepted. The alternative hypothesis, that these factors do influence smallholder farmers' participation in the Cotton YIELD Programme, is statistically significant and cannot be rejected. The (b) null hypothesis is that the Cotton YIELD Programme has not increased the agricultural net income of the smallholder cotton farmers in Zambia. However, the analysis in this study has shown that the Cotton YIELD Programme has significantly increased the agricultural net income of the participants by 38.1 %, as reported in Table 6.2 above. Based on this empirical evidence, the latter-stated null hypothesis cannot be accepted. The alternative hypothesis that the Cotton YIELD Programme has increased agricultural net income is statistically significant and is not rejected.

The positive impact of the Cotton YIELD Programme suggests that participating in the Cotton YIELD Programme might be an imperative pathway through which smallholder cotton farmers could increase their agricultural net incomes. Nevertheless, participating in the Cotton YIELD Programme is mainly constrained by distances to extension agents and market outlets. Comparatively, female-headed households were observed to have smaller farm sizes to farm on than male-headed households have. The study also revealed that access to credit remains a challenge for smallholder farmers, as only 21.3 % of the farm households sampled have access to credit. Owing to this, policy interventions that address this constraint could accelerate participation in the Cotton YIELD Programme and consequently increase agricultural net income.

7.2 Recommendations

The results of this study are important for designing policies that promote the adoption of improved technologies of the Cotton YIELD Programme so as to increase smallholder cotton farmers' agricultural net income. This should be motivated by the results of the study that the Cotton YIELD Programme has increased the agricultural net income of smallholder cotton farmers by 38.1 %. This calls for serious participation in the Cotton YIELD Programme, if smallholder farmers are to increase their agricultural net income. Firstly, this study recommends that Dunavant Zambia Limited (DZL) should continue with the Cotton YIELD Programme and scale it up so that more smallholder farmers can benefit from the programme. Secondly, DZL needs to address the constraints, such as distances to extension agents and market outlet, as the company continues with the programme so as to improve the spread and intensity of participation in the Cotton YIELD Programme. Consequently, the programme may have more impact on agricultural income. Thirdly, the study recommends that government should address challenges of access to credit by mobilising smallholder farmers to form formal co-operatives so as to accelerate access to credit and consequently increase agricultural net income. This is because the results show that the majority of farmers had accessed credit through local farmer organisations. Fourthly, concerted efforts are needed by government to address land inequality to enable land-constrained female smallholder farmers acquire additional land.

7.3 Future Research

In sub-Saharan African (SSA), smallholder farmers operate under conditions of risk and uncertainty. Therefore, continuous monitoring of the impacts of new technologies on agricultural income is imperative. To understand the full impact of the Cotton YIELD programme, there is need for future research to consider increasing the sample size so as to cover all the districts in which the Cotton YIELD programme has been introduced. Furthermore, future research should consider measuring and quantifying the indirect impact of the Cotton YIELD programme, for example, the impact of an increase in farm wages on employment and the multiplier effects of rural households. From an analytical and academic point of view, a question that needs attention is the causality between variables included in this study. For instance, research should be carried out on the cause and effect between the presence of animal traction, wealth and adoption of new technology.

REFERENCES

Aldana, U., Fortz. J. D., Baham, L. B. & Useche, P. 2010. Sequential adoption of package technologies: Dynamics of stacked traint corn adoption. University of Wisconsin.

Asfaw, S. & Shiferaw, B. 2010. Agricultural Technology Adoption and Rural Poverty: Application of an Endogenous Switching Regression for Selected East African Countries. Paper presented at the Joint 3rd African Association of Agricultural Economists (AAAE) and 48th Agricultural Economists Association of South Africa (AEASA) Conference, Cape Town, South Africa, September 19-23, 2010.

Awotide, B. A., Diagne, A., Awoyemi, T. T. & Ojehomon, V. E. T. 2012. Impact of Access to Subsidized Certified Improved Rice Seed on Income: Evidence from Rice farming Households in Nigeria. OIDA International Journal of Sustainable Development, 2 (12), 43-60.

Baker, J. 2000. Evaluating the impact of development projects on poverty. World Bank, Washington DC.

Barret, C.B., Moser, C. M., McHugh, O.V. & Barison, J. 2004. “Better Technology, Better Plots or Better Farmers?” USAID.

Beaman, L. & Dillon, A. 2014. The diffusion of agricultural technologies within social networks: Evidence from compositing in Mali. IFPRI. 1-4

Becerril, J. & Abdulai, A. 2010. The impact of improved maize varieties on poverty in Mexico: A propensity score matching approach. World Development, 38(7), 1024–1035.

Bercerril, J. & Abdulai, A. 2009. The impact of improved maize varieties on poverty in Mexico: A propensity score marching approach. World Development, 38 (7), 1024–1035.

Brookhart, A. M., Schneeweiss, S., Rothman, K. J., Glynn, R., Avorn, J. & Sturmer, T. 2006. Variable Selection for Propensity Score Models. *American Journal of Epidemiology* 12:1149–1156.

Chirwa, E.W. 2005. Adoption of fertilizer and hybrid seeds by smallholder maize in southern Malawi. Development in Southern. Africa. 22 (1), 1–12.

CSO. 2010. Living conditions monitoring survey report 2006 and 2010. Lusaka, Zambia.

Davis, K. 2008. Extension in sub-Saharan Africa: Overview and assessment of past and current models and future prospects. *Journal of International Agricultural and Extension Education*, *15*(3), 15–28.

Davis, K., Nkonya, E., Tato, E., Mekonnen, D. A., Odendo, M., Miiro, R. & Nkuba, J. 2012. Impact of farmer field schools on agriculture productivity and poverty in East Africa. *WD Journal,* 4(2): 4002-4413.

Darr, D. & Chern, W. 2000. Estimating adoption of GMO soybeans and corn: a case study of Ohio, USA. In: 4th International Conference on the Economics of Agricultural Biotechnology, 824–843.

Doss, C. R. & Morris, M. L. 2001. How does gender affect the adoption of agricultural innovations? The case of improved maize technology in Ghana. *Journal of Agricultural Economics*, *25*(1), 27–39.

DZL. 2015. Improving smallholder cotton yields in Zambia: YIELD/ Cotton made in Africa programme, Lusaka Zambia. Presentation. [Online] Available: http/www.slidesserve.com/dyllis/yield. [Accessed: 2015, 10March]

Elias, A., Nohmi, M., Yasunobu, K. & Ishida, A. 2013. Effect of agricultural extension programme on smallholders' farm productivity: Evidence from three peasants, S.Afr. Tydskr. Landbouvoorl. /S. Afr. *J. Agri. Ext.* Vol. 42, No 2, (2014): 62 – 80.

Feder, G., Just, R. E., & Zilberman, D. 2006. Adoption of agricultural innovations in developing countries: a survey. Econ. Dev. Cult. Change 33, 255–298.

Fisher, M. & Kandiwa, V. 2013. Can agricultural input subsidies reduce the gender gap in modern Maize production? Evidence from Malawi: Food policy 45 (2014) 101-111.

Foster, A.D. & Rosenzweig, M. R. 2010. Microeconomics of technology adoption. Annu. Rev. Econ. 2, 395–424.

Gerhart, J. D. 1975. Diffusion of hybrid Maize in Western Kenya. PhD. Thesis. Princeton University.

Haggblade, S., Hazell. P. & Dorosh, P. 2007. Sectoral growth linkages between agriculture and the rural nonfarm economy in transforming the rural nonfarm economy: Opportunities and threats in the developing World, ed.

Haggblade, S., Kabwe, S. & Plerhoples, C. 2011. Productivity impact of conservation farming on smallholder cotton farmers in Zambia. FSRP, working paper number 47.

Hardaker, J. B., Huirne, R. B. M., Anderson, J. R. & Lien, G. 2004. Coping with risk in agriculture. 2nd Edition, CAB International, New York. (Abbr. FMA).

Hassan, R. M. 2015. Sampling procedures and survey design. Teaching notes for part 2. Department of agricultural economics, University of Pretoria.

Heckman, J. J. 1979. Sample selection as a specification error.Econometrica.47(1): 153-161.

Hossain, M., Lewis, D., Manik, B. L & Alamgir, C. 2003. Rice research, technological progress, and impacts on the poor: the Bangladesh case. Discussion paper 110. International Food Policy Research Institute (IFPRI).

IFAD. 2011. Rural poverty report: New realities, opportunities and challenges for tomorrow' generation. IFAD, Rome.

IFAD. 2001. Rural development reports: Role of agriculture in poverty reduction. IFAD, Rome.

ILO. 2015. Measuring progress in the fight against Child Labour. ILO, Geneva.

Imbens, G.M. & Woodridge, J.M. 2008. “Recent development in the econometrics of programme evaluation. Working Paper 14251.[Online] Available: http://www.nber.org/paper/w14251[Accessed: 2015, 9 January].

Janaiah, A., Hossain, M. & Otsuka, K. 2006. Productivity impact of the modern varieties of rice in India. Developing Economies, 64(2), 190–207.

Kassie, M., Shiferaw, B. & Geoffrey, M. 2011. Agricultural Technology, Crop Income, and Poverty Alleviation in Uganda. World Development, forthcoming.

Khandker, S.R., Koolwal, G.B. & Samad, H. 2010. Handbook on impact evaluation quantitative methods and practices, World Bank, Washington DC.

Kirsten, J. F., Dorward, A. R., Poulton, C. & Vink, N. 2009. Institutional economics perspectives on Africa agricultural development. IFPRI.

Kishindo, P. 2004. Customary land tenure and the new land policy in Malawi. *Journal of Contemp. A. Stud.* 22 (2), 213–225.

Langyintuo, A. S. & Mungoma, C. 2008. The effect of household wealth on the adoption of improved maize varieties in Zambia. *Food Policy, 33*(6), 550–559.

Lee, M. J. 2005. Micro-econometrics for policy, programme and treatment effects. advanced texts in econometrics. Oxford University Press.

Lozano, A. 2012. Leveraging a cotton out-grower model for Malaria Control: growing inclusive markets. Lusaka, Zambia.

MAL. 2013. National Agriculture Investment Plans (NAIP). Lusaka, Zambia.1-45.

MAL-Ministry of Agriculture and Livestock, IAPRI-Indaba Agricultural Policy Research Institute, World Bank, UNZA-University of Zambia. 2012. “Livestock sector in Zambia for economic growth and poverty reduction: An Analysis”

Marra, M., Pannell, D. J. & Ghadim, A. 2002. Economics of risks, uncertainty and Learning in the adoption of new technologies. Department of agriculture and resource economics. North Carolina State. USA.

Mendola, M. 2006. Agricultural technology adoption and poverty reduction: A propensity – score matching analysis for rural Bangladesh. Food policy 32 (2007) 372-393.

Muhammad, S, Chaudhry, K. M, Khatam, A & Ashraf, I. 2013. Impact of farmer field school on social wellbeing of farming community in Khyber Pakhtunkhwa, Pakistan. Journal of Animal and Plant Sciences, 23 (1) 319-323.

Ndoro, J. T., Mudhara, M. & Chimonya, M. 2014. Livestock extension programmes participation and impact on smallholder cattle productivity in KWAZULU-NATAL: S.Afr. Tydskr. Landbouvoorl. /S. Afr. *J. Agri. Ext.* Vol. 42, No 2.

Nell, W. T., Van Schalkwyk, H. D., Sanders, J. H., Schwalbach, L. & Bester, C. J. 1999. Adoption of veterinary surgeon services by sheep and goat farmers in QwaQwa. University of Free State, South Africa.

Ng’ombe, J. 2013. Impact of conservation farming on smallholder farm households’ income in Zambia: evidence using an endogenous switching regression model. M.Sc. Thesis. University of Zambia.

Nyanga, P. H., Johnsen, F. H., Aune, J. B. & Kalinda, T. H. 2011. Smallholder farmers: perceptions of climate change and conservation agriculture: Evidence from Zambia. *Journal of Sustainable Development* 4 (4): 73-85.

Ogada, J. M., Mwabu, G. & Muchai, D. 2014. Farm technology adoption in Kenya: A simultaneous estimation of inorganic fertiliser and improved Maize variety adoption decisions. *Journal of Agricultural and Food Economics,* 2:12.

Peltger, R. & Rottger, D. 2013. Cotton sector organisation models and their impact on productivity and income. Germany development institute. Discussion paper, 4 (2013).

Pender, J. L & Kerr, J. M. 1998. Determinants of farmers' indigenous soil and water Conservation investment in semi-arid India, Agricultural economics 19: 113-125.

Peterman, A., Behrman, J. & Quisumbing, A. 2010. A review of empirical evidence on gender differences in nonland agricultural inputs, technology, and services in developing countries. IFPRI Discussion Paper 00975.

Place, F., Otsuka, K. 2010. Tenure, agricultural investment, and productivity in the customary tenure sector of Malawi. Econ. Dev. Cult. Change 50 (1), 77–100.

RATES. 2003. Regional agricultural trade expansion support programme, *Cotton Textile-Apparel Value Chain Report.* Zambia, [Online] Available: (http://rates@ratescentre.org/). [Accessed: 2015, 30 March.]

Ravallion, M. 2002. Assessing the poverty impact of assigned programme. The Work Bank, Washington DC.

Ravallion, M. 2001. Mystery of the vanishing benefits: An introduction to evaluation. World Bank Economic Review, 15(1): 115-140.

Rosenbaum, P. R. 2002. Observational studies. 2nd edition. Springer-Verlag. New York.

Rosenbaum, P. & Rubin, D. 1983. The central role of the propensity score in observational studies for Causal Effects. *Biometrika,*70: 41-55.

Rubin, D. 1974. Estimating causal effects of treatments in randomised and non-randomised studies. *Journal of Educational Psychology*, 66: 688-701.

Rubas, D. 2004. Technology Adoption: Who is likely to adopt and how does timing affect the benefits? PhD Thesis, Texas A&M University.

Simtowe, F., Kassie, M., Asfaw, S., Shiferaw, B., Monyo, E. & Siambi, M. 2012. Welfare effects of agricultural technology adoption: The case of improved groundnuts varieties in rural Malawi. Selected paper prepared for presentation at the International Association of Agricultural Economists (IAAE) Triennial Conference, Brazil, 18-20 August 2012.

Smale, M. 2011. Does household headship affect demand for hybrid maize seed in Kenya? An exploratory analysis based on 2010 survey data. Michigan State University Working Paper 115, East Lansing, MI.

Tschirley, D. & Kabwe, S. 2009. Cotton sector of Zambia, FSRP African Region, Working Paper No 124.

Tschirley, D. & Kabwe, S. 2007. Cotton in Zambia: Assessment of its organisation, performance: Current policy initiatives, and challenges for the future, FSRP Working Paper, No 26.

Wooldridge, J. M. 2013. Introductory econometrics*:* Modern approach, 5th Edition. Michigan State University, USA.

World Bank. 2012a. World Development Report: Agriculture and Development. The World Bank, Washington DC.

World Bank. 2012b. World Development Report: Gender Equality and Development. The World Bank, Washington, DC.

World Bank. 2008a. World Development Report. Agriculture for development. The World Bank, Washington, DC.

World Bank. 2008b. World Development Report: Jobs and Development. The World Bank Washington DC.

World Bank. 2006. Ethiopia: Policies for pro-poor agricultural growth. The World Bank. Washington, DC.

APPENDICES

Appendix 1: Description of Variables

Variable name	Variable Description	Expected sign
Dependent variables		
Log crop net Income	Log crop net Income	
Participation	Participant dummy, one if yes and otherwise zero	
Independent Variables		
Demographics Characteristics		
Age of the Decision Maker	Age of the Decision Maker in years	±
Gender of the Decision Maker	Gender of the decision maker equal to one if male and zero otherwise	+
Education level of the Decision Maker	Education level of the Decision Maker in years	+
Marital status of the Decision	Marital status of the Decision Maker equal to one if single, and zero otherwise	-
Family size	Family size	±
Wealth variables and farm characteristics		
Land cultivated	Land cultivated in hectares	+
Farm size	Farm size in hectares	+
Active family Labour	Active family Labour in adult equivalents	+
Own animal traction	Own animal traction equal to one if yes and zero otherwise	+
Access to off-farm income	Access to off-farm income equal to one if yes and zero otherwise	±
Assets value	Assets value in Zambia kwacha	+
Institutional and access related variables		
Distance to local markets outlets	Distance to local markets outlets in kilometers	-
Distance to extension agents	Distance to extension agents in kilometers	-
Access to credit	Access to credit equal to one if yes and zero otherwise	+
Membership to farmer organization	Membership to farmer organization equal to one if yes and zero otherwise	+

Appendix 2: Characteristics of Participants and Non-participants after Matching

Variable Description	Mean Participants	Mean Non-participants	P-values for mean difference
Number of observations	126	174	
Independent Variables			
Demographic characteristics			
Decision Maker' age in years	44.44	43.14	0.261
Gender of the Decision Maker (1=male, 0=otherwise)	0.57	0.67	0.092*
Level of education level of the Decision Maker in years	6.39.	5.92	0.300
Marital status of the Decision Maker (1=single, 0=otherwise)	0.08	0.10	0.514
Family size	5.80	5.83	0.897
Household wealth variables and farm characteristics			
Land cultivated (ha)	1.65	1.75	0.274
Farm size (ha)	4.76	4.80	0.909
Active family Labour (Adult equivalents)	5.06	4.83	0.310
Own animal traction (1=yes, 0=otherwise)	0.59	0.69	0.189
Access to off-farm income (1=yes, 0=otherwise)	0.40	0.27	0.230
Own radio or Television set or mobile phone	0.1	0.04	0.079*
Assets value (ZMK00)	7.44	5.93	0.990
Institutional variables and access related variables			
Distance to local markets outlets (km)	1.56	1.28	0.229
Distance to extension agents (km)	2.33	2.50	0.125
Access to credit (1=yes, 0=otherwise)	0.39	0.05	0.516
Membership to farmer organisation (1=yes, 0=otherwise)	0.87	0.87	0.853

* Statistically significant at 10 %, ** at 5 % and *** at 1 %. Note standard errors are in parentheses

Source: Author's calculations, baseline data from DZL, 2005 and follow-up survey, 2015

Appendix 3: Questionnaire

Serial No:__________

Date of interview ____________

AN ECONOMIC EVALUATION OF THE COTTON YIELD PROGRAMME IN ZAMBIA:

LEK 890 Dissertation (James Ngulube)

Department of Agricultural Economics, Extension and Rural Development

University of Pretoria

Dear Respondent,

You have been randomly selected as part of the sample to fill in this questionnaire on the topic stated above. Therefore you are kindly requested to answer this questionnaire as truthfully as possible. Be assured that the information you provide will be treated confidentially.

Household Identification

1.1 Region name: _____________ Region code **regn** **[ ]**

1.2 District Name: ________ District Code **dist** **[ ]**

1.3 Shed Area name: __________ Shed Area code **shed** **[ ]**

1.4 Village name: ________ Chiefdom: ___________

1.5 Household code: ________ **hh [**]

1.6 (a) When was the household head born? __/___/__ **age [ ]**

(b) Sex of household head sex [ ] (0=Female; 1=Male)

1.7 What is the education level of the household head?___________ **Ed [ ]**

0. None 1. Primary 2.Secondary 3. Tertiary

1.8 What is the marital status of the household head?____________ **mstat** [

1.Single 2. Married 3.Divorced 4. Widowed 5.Separated

6. Others specify___

1.9 What is the main occupation of the household head? _______ **occu** [ ]

1.10 Is the household head the decision maker? **dm [ ]**

0. No 1. Yes

1.11 Is the household head the main respondent? **rown [ ]**

0 = No

1= Yes $\boldsymbol{If\ \ answer\ to\ 1.9\ is\ Yes,\ \ go\ to\ question}$ 1.15

1.12 Relationship to the household head _______________ **d [ ]**

1.13 What is the education level of the respondent?___________ **d1 [ ]**

0. None 1. Primary 2.Secondary 3. Tertiary

1.14 What is the marital status of the respondent? **d2 [ ]**

1.Single 2. Married 3.Divorced 4. Widowed 5.Separated

6. Others, specify ________

1.15 When was the respondent born? __/___/___ **d3 [ ]**

1.16 Has the household head participated in the Cotton YIELD Programme?

P [ ]

1=Yes;

$0 = No$ $\boldsymbol{If\ \ answer\ is\ no, go\ to\ question\ 1.17}$

1.17 How long has the household head been participating in the Cotton YIELD programme?

__Years **d3 [ ]**

1.18 How does the household head rate the quality of extension services of the Cotton YIELD programme to other extension programmes? **Percp**1 [ ]

1. Below average 2. Average 3. Above average

2.0 Demographics: I would like to ask few questions about each member of the household (Household is defined as those members that eat from the same pot)

Can you please provide me with information on the members of this household? ***Start with the household head***.		What is ...'s sex? 0=Female 1=Male	When was ... born?	What is ...'s marital status? 1=Single/under-age 2=Married 3=Divorced/separated 4=Widowed	What is the highest level of education attained by ... in years? ***See code below***	What is ...'s relationship to the head? ***See code below***	Did … provide farm labour in the 2014 farming season 0=No 1=Yes	Did … earn off-farm income the 2014 farming season	Which year did … start the income activity **(e.g. 2004),**
Member codes	**Member name**	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**		

Relationship to the househead

1=Head
7=Nephew/Niece
2=Spouse
8=Son/daughter in law
3=Own child
9=Grandchild
4=Step child 10=Others specify
5= Parent
6= Brother/Sister

2.0 Farm Characteristics and Field Practices

3.0 What is the size of your farm?

_______ ha **ha1** [ ]

3.1 How many hectares of land did you cultivated in the 2013/2014 farming season?

ha2 [ ]

a) Own _______ ha **ha** [ ]

b) Hire _______ ha **ha1** [ ]

3.2 What was the main tillage method did you use to prepare the cotton field last season?

AT [ ]

1. Hand hoe 2. Animal Traction 3. Zero tillage 4. Others specify ……..

3.3 When was tillage done in your cotton field last season? **B1 [ ]**

1 Before first rains 2. At the onset of first rains 3. After the first rains

3.4 When did you plant cotton seed last season? **B2 [ ]**

1 Before first rains 2. At the onset of first rains 3. After the first rains

3.5 What type of labour did you mainly use in your cotton field last season? **Hb** [ ]

1. Family labour 2.Hired labour 3.Both Family and Hired labour

3.6 Did you use to spray the cotton field last season? **Sp**[ ]

1= Yes;

0= No $\boldsymbol{If\ answer\ is\ no, Go\ to\ question\ 5.8}$

3.7 If yes, what type of sprayer did you use to spray in the cotton field? **Sp1** [ ]

1. Jacto knapsack sprayer 2.ULVA+ sprayer 3.Others, specify______

3.8 How many times did you spray the cotton field? **Sp2 [ ]**

1.Once 2.Twice 3.Thrice 4. Four times

5. Five times 6. Six times 7. More than six times

3.9 Did you use to scout before spraying? **Sp3** [ ]

0 = No 1= Yes

3.10 What crop did you plant in the cotton Field in 2012/2013 farming season? **Sp4** [ ]

1. Cotton 2. Sorghum 3. Soya beans 4. Maize 5. Sunflower

6. Groundnuts 7. Other, specify ………………

4.0 For how long have you been growing Cotton?
______ Years **Sp5 [ ]**

4.0: Crop Sales, Stocks and purchases (I now would like to ask a few questions on crop sales, prices and purchases and major buyers /sellers)

	Did the HH grow…. Last season?	Total hectare of ….cultivated last farming season	Amount of …..harvested last season	Unit **Code below**	What was the total cost incurred in producing ….last season? (ZMK)	Did the HH sell this crop in the last last farming season? 1=Yes 0=No	Qty sold	Unit **Code below**	Price at the largest sale (ZMK/unit)	Qty of …in stock now
CROP	**FD01**	**FD02**	**FD03**	**FD04**	**FD05**	**FD06**	**FD07**	**FD08**	**FD09**	**FD10**

Crop codes (Crop)	**Unit codes (FD4; 08; 11)**	
1= Seed cotton 2= Maize 3=Sunflower 4=Groundnuts 5=Soyabeans 6=Others, specify	1=90 kg bag 2=50 kg bag 3=25 kg bag 4=10 kg bg 5=20 litre tin 6=5 liter gallon 7=MEDA 8=Bunch	9=Muchumbu 10=’Ka BP’ 11=Crate 12=Tonne 13=Box 14=Number 15=Kilogram

6.0 Livestock Assets

Livestock type	How many… did the hh have in December 2013?	How many… does the hh have last december 2014?	How many… did the hh sell during 20013/014 season? Enter '0' if none	How much did the hh earn from the sale of… during 20013/014 season? (ZMK)	How many… died during 20013/014 season?	How many… did the hh consume during 20013/014 season? Enter '0' if none	How many… did the hh give away during 20013/014 season?	How many… did the hh receive as gifts during 20013/04 season?	How many… did the hh purchase during 20013/014 season? Enter '0' if none	*What was the total value of... purchased? (ZMK)*
Codes	**OL01**	**OL02**	**OL0301**	**OL04**	**OL05**	**OL06**	**OL07**	**OL08**	**OL09**	**OL10**
Cattle										
Pigs										
Sheep										
Goats										
Poultry										
Donkey										
Others, specify										

7.0 Access to Information, Credit and Membership

7.10 How far is the main local market from your homestead? **AI [ ] km**

7.11 How long does it take you to get to the main road by motorized vehicle in the?

a) Dry season (minutes)? **AI1 | | minutes**

b) Rainy season (minutes)? **AI2 | | minutes**

7.12 How far is the nearest extension agent from your homestead? **AI3 [ ]**

______________km

7.13 How many times were you visited by extension agent last farming season? **AI4 [**

1. None 2. Once 3. More than once

7.14 Do you have access to credit/loans? **AC1 [ ]**

0=No; 1=Yes

7.15 When did you start having access to credit/loans? **AC2 [ ]**

1. Before 2005 2. After 2005

7.16 What is the name of the financial institutions that provides credit/loans in your area?

______________ _______ **AC3 [ ]**

7.17 What was the last amount of loan/credit did you obtain? K**_______AC4 [ ]**

7.18 How many times have you defaulted in paying back the loan **AC5 [ ]**

1. None 2. Once 3. More than once

7.19 Are you a member of any farmer organisation in your area? AC6 [ ]

0. No 1. Yes

7.20 If **yes,** when did you become a member of the farmer organisation? **AC7 [ ]**

1. Before 2005 2. After 2005

7.21 **Physical/capital asset** (Fill in the following table about the household's non-livestock assets)

Asset type		Does the hh have…? 0=No 1=Yes	Approx. what is the current value of all the…s? (ZMK)	How many …s did the hh own in December last year?	Approx. what was the value of all the… in December last year? (ZMK)	Did the hh sell… in 20013/014 season? 0=No 1=Yes	How much did the hh earn from the sale of …? (ZMK)
Asset	**Name/Descriptiion**	**AS01**	**AS02**	**AS03**	**AS04**	**AS05**	**AS06**
1	Tractor						
2	Truck/pick up						
3	Tractor trailer						
4	Ox-drawn implements						
5	Ox-cart						
6	Yenga press						
7	Television set						
8	Radio						
9	Sewing machine						
10	Mobile phone						
11	Bicycle						
12	Treadle pump						
14	Chairs/sofa						
15	Wardrobe						
16	Display unit						

17	Others, specify						

8.1 Do you own animal traction? **Own [ ]**

0. No 1. Yes

THANK YOU VERY MUCH FOR YOUR COOPERATION!!