J Agri Sci, 11, 12(1-2): 1-12 (2020, 2021)
PRINT: ISSN 0976-6898 ONLINE: ISSN 2456-6535
DOI: 10.31901/24566535.2020-21/11-12.1-2.131

Impact Assessment of the Cotton YIELD Programme in Zambia*

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KEYWORDS Counterfactual. Propensity Score. Self-Selection. Treatment Effect

ABSTRACT This paper sought to evaluate the economic impact of the Cotton YIELD Programme on crop income of smallholder cotton farmers in Zambia. Specifically, the study sought to (a) identify factors that influence smallholder cotton farmer' participation in the programme and (b) determine whether the Cotton YIELD Programme has increased the income of smallholder cotton farmers in Zambia. The study utilized pooled cross-section data of 300 cotton farmers, collected from two households survey (2005 and 2015) in Mumbwa district of Zambia. The Double Difference model combined with Propensity Score Matching methods were employed in the analysis. Results show that participation in the programme is positively driven by education, farm size, membership, access to credit, ownership of animal traction and media. However, distance to extension agents and market outlets negatively influence participation. Furthermore, the study found that the Cotton YIELD Programme has significantly increased crop income of smallholder cotton farmers by 38.1 percent.

INTRODUCTION

Rural poverty worldwide remains a challenge and become predominantly Africa phenomenon. In Zambia, the current levels of poverty are extremely high. Recent economic growth, which made Zambia reach the lower-middle-income status, has not translated into significant inclusive development. Although the country had significant improvement in poverty reduction from 50 percent in 2016 to 44 percent in 2020, poverty levels among rural dwellers remain pronounced at 59 percent (Ministry of National Development Planning [MNDP] 2020). Furthermore, the gap between urban and rural poverty continues to widen. Zambia's Gini index at 57.1 over 2010-2017 indicates that income distribution remains unequal. To address the poverty problem, several strategies are well documented on how to remedy and alleviate the issues giving rise to poverty (World Bank 2019). Recommendations from World Bank over the years have included topics on improving agricultural productivity growth via improved inputs (World Bank 2019). However, in most developing countries, smallholder farmers have almost no access to seasonal credit to finance improved input purchases (World Bank 2014). They only gain access to markets and improved inputs through Out-grower schemes. In Zambia, one of the most important cash crops grown via out-grower schemes is cotton. However, cotton productivity (yield per hectare) at farm level remains low, resulting in low agricultural income.

In 2005, DZL with funding from the German Development Agency (GTZ), introduced the Cotton Yield Improvement through Empowerment, Learning and Discipline" (YIELD) Programme in Zambia. The programme is also part of the "Cotton Made in Africa" project (Tschirley and Kabwe 2009). The Cotton YIELD Programme is a package of improved practices. The transfer of knowledge of improved agricultural technologies of the programme have been through trainings conducted by DZL. The Cotton YIELD Programme has had over 42 000 beneficiaries (DZL 2015). The aim of the Cotton YIELD Programme is to increase agricultural income of smallholder cotton farmers through increased cotton productivity (yields per hectare), Nevertheless, 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

* The paper is prepared from my thesis which can be accessed on https://repository.up.ac.za/handle/2263/60846. The thesis entitled "An economic evaluation of the Cotton YIELD Programme in Zambia" is by James Ngulube, submitted to the University of Pretoria, South Africa under the supervision of Prof Chris Blignaut.

with 538 kg/ha for non-adopters. However, Manda et al. (2016) observed that higher productivity achieved by adopters of improved technology did not always translate into higher agricultural 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 income per participant cotton farmer.

Furthermore, earlier studies (for example, Nyanga et al. 2011; Haggblade et al. 2011) on whether technology transfer programmes had contributed to increased agricultural 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 might have resulted in biased conclusions about the impact of improved technology transfer programmes in Zambia. To avoid such potential pitfalls, this study used the Double Difference (DD) method, combined with Propensity Score Matching (PSM) methods to evaluate the impact of the Cotton YIELD Programme.

Study Objectives

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

Specific Objectives

Specifically, the study sought:

(a) to identify factors that influence smallholder cotton farmer' participation in the Cotton YIELD Programme.

(b) to determine whether the Cotton YIELD Programme has increased the income of smallholder cotton farmers in Zambia.

The rest of this paper is organized as follow. The next section describes the conceptual framework that illustrates the main task of the programme in Zambia. The methodological section outlines the econometric procedures employed to estimate the impact of the Cotton YIELD Programme on agriculture income. Besides, it outlines the study area, sampling procedure, data collection and data collection limitations. The results and discussion section provide and discusses the estimates of the impact of participation in the Cotton YIELD Programme. The last section summaries the main findings and draws some policy implications and outlook for future research.

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 maximization framework (Ogada et al. 2014). Based on the expected utility maximization 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 which might lead to self-selection into the Cotton YIELD Programme (Kassie et al. 2011; Khandker et al. 2010). 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 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.

Conceptual Framework

Agricultural income is defined as the sum of income from crops and livestock (Davis et al. 2012). However, crop income was used as a proxy for agricultural income in this study after adjusting for inflation because the focus of the Cotton YIELD Programme is to enhance crop income (DZL 2015). Crop 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:

$$E(Y) = E(Y1i - Y0i / Pi = 1) \quad \text{Equation 3.1}$$

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, 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.

Randomization 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:

$$E(Y) = E(Y1i - Y0i \mid X, Pi = 1) \quad \text{Equation 3.2}$$

The assumption of Equation 3.2 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 income between participants and non-participants with similar values of the covariates to the Cotton Yield Programme. A more appealing version of Equation 3.2 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:

$$P(X) = P(P = 1, X) \quad \text{Equation 3.3}$$

where P is the propensity score.

The standard PSM procedures as described by Ravallion (2002) was followed in selecting a 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 propensity score. Several versions of balancing tests exist in literature (Ng'ombe 2013). However, Rosenbaum and Rubin (1983) suggested a standardized mean difference between participants and non-participants of not greater than 20 percent, as above 20 percent was an indication of failure of the matching process. 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 income of the Cotton YIELD Programme non-participants without and with the programme from participants, as shown in Equation 3.4.

$$\begin{aligned} E(Y) = {} & E(Y1i - Y0i \mid Pi = 1) \\ & - E((Y1i - Y0i \mid Pi = 0) \end{aligned} \quad \text{Equation 3.4}$$

where $(Y_{1i}\text{-}Y_{0i}|P_{i=}1)$ is the expected difference in agricultural income of participants and nonparticipants with the programme, whereas $(Y_{1i}\text{-}Y_{0i}|P_{i=}0)$ is the expected difference in agricultural income variable of participants and non-participants without the programme, and E(Y) is the impact estimate also known as ATT

(Wooldridge 2013). The growth in agricultural income 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:

$$T = E(Y0i|Pi = 1 - Y0i|X, Pi = 0) \quad \text{Equation 3.5}$$

where ($Y_{0i}|P_{i=}1$) is the agricultural income with the programme, ($Y_{0i}|P_{i=}0$) is agricultural income without the programme for non-participants, and T is the bias due to unobservable factors. In the absence of unobserved bias (T=0), agricultural income with the programme ($Y_{0i}|P_{i=}1$) is expected to be equal to agricultural income without 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.

MATERIAL AND METHODS

Study Area, Data and Sampling Procedure

This study was conducted in Mumbwa district of the Central province of Zambia, located in agro-ecological region IIa. The district receives between 750 and 1000 mm of rainfall per year, making it suitable for cotton production (World Bank 2018). The district has seven operational DZL shed areas manned by shed area managers and with more than 7,000 Cotton YIELD Programme farmers. 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.

Both secondary and primary data were used in the study. Secondary data came from documentary reviews and baseline survey conducted by DZL in 2005. Primary data was collected through a sampled household survey conducted in the 2015 agricultural season. The follow-up survey was conducted on different households from those interviewed in the baseline survey so as to expand the sample size. The random sampling procedure was employed in selecting observations into the sample to ensure precision of results and also the same procedure was employed in the baseline survey. The stratified random sampling procedure was undertaken by first splitting the sampling frame 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 representatives (Hassan 2015). 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 DZL in 2005. Data was collected on crop and livestock production, costs of production, demographics, wealth-related factors and farm characteristics as well as on institution and access-related factors. The study employed PSM procedures in the selection of the comparison group based on predicted propensity of participating (Ravallion 2002) and the Double Difference (DD) method to correct for differences in the unobserved covariates.

RESULTS AND DISCUSSION

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 1 in Appendices. Some of these selected variables (to be named later) are also used as independent variables in the estimate models to be presented later and were selected on the basis of theoretical discussions. This study analyzed a dataset of 300 smallholder cotton farmers; of these, 42 percent are Cotton YIELD Programme participants, while 58 percent were non-participants, as reported in Table 1 in Appendices.

Demographic Characteristics of Participants and Non-participants

The demographic characteristics of participants and nonparticipants differ significantly

(See Table 1 in Appendices). Average years of education for participants was 7.75 years, and 6.39 years for non-participants and the difference was statistically significant at 5 percent 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 participants, compared with participants, were married and the difference is statistically significant at 5 percent. The results suggest that being married might influence participation decisions in the Cotton YIELD Programme positively. Married household heads have more labour and therefore were more likely to adopt new technologies (World Bank 2012).

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 were statistically significant. On average, participants had larger farm sizes of 2.75 hectares, whereas non-participants have 1.09 hectares. Thus, it 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 World Bank (2016) in Zambia that adopters of improved technologies had larger farm sizes than non-adopters do. Similarly, participants had greater asset values and numbers of farm workers (labour) than non-participants. The average active, family labour for participants is 5 adult equivalents, compared with 4 adult equivalents for nonparticipants. In addition, 59 percent of the participants own animal traction, compared with 30 percent for non-participants, and the difference was 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 own 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 and Shiferaw 2010). Therefore, possession of a media instrument may have a positive effect on participation decision in the Cotton YIELD Programme.

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

Institutional and access-related factors analyzed in Table 1 in Appendices 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 percent for nonparticipants, suggesting that access to credit is positively associated with participation decisions. Similarly, participants are nearer to extension agents and market outlets than nonparticipants and the difference was statistically significant. Membership of a local farmer organization facilitates informal exchange of information among farmers. The results also show that a significantly high proportion of participants (87%) were members of local farmer organizations, against 42 percent 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 critical in the diffusion of new technologies among farmers.

Outcome Variables

The outcome variable analyzed is real crop income, also referred to as real net farm income. The results from the analysis of the observed outcome variable are reported in Table 2 in Appendices. The results show significant differences in average crop income between participants and non-participants of the programme. On average, participants of the Cotton YIELD Programme achieve higher profits of ZMK1,813.40 per hectare, compared with ZMK806.39 per hectare 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. (2011) 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 that participants and non-participants differ significantly. The heterogeneity in observable characteristics between the two groups may be attributable to endogeneity or self-selection. Self-selection, if not accounted for, could lead to biased conclusions about the impact of the Cotton YIELD Programme on agricultural income (Asfaw and Shiferaw 2010; Ravallion 2001). Therefore, these findings motivated this study to use Propensity Score Matching (PSM) to control for heterogeneity in observable characteristics to obtain robust results. PSM removes heterogeneity by balancing the observed covariates between nonparticipant and participant (Ravallion 2001)[1]. Therefore, it is the obvious method of selecting the comparison group in Double Difference studies.

Estimation of Propensity Scores

One of the specific objectives of this study is to identify 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 participation dummy variables 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 analyzing the marginal effects also known as elasticities which are partial first order derivatives of the probability function, evaluated at the sample means (Green and Alston 1990). The results from the estimated Probit model are summarized in Table 3 in Appendices. The results show that log likelihood and pseudo R^2 are -114.99 and 0.44 respectively. The model is statistically significant with a 99 percent 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 hypothesized to influence participation decisions have the expected signs as discussed previously based on Table 1 in Appendices and therefore could not be discussed further.

Propensity Score Matching

In order to deal with the observable heterogeneity in the initial conditions of the two groups Propensity Score Matching was used. The results from the P-score are reported in Figure 1 in Appendices. The co-ordinates of the propensity scores (X-axis) and the densities of the scores (Y-axis)[2] indicate density distribution of propensity scores, and a region of common support is seen where the two groups overlap. The bottom half of Figure 1 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][3] 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 1 only shows observations that fell within the region of common support. A balancing test was also conducted to assess the quality of matching using the p-values of standardized mean difference and the likelihood ratio tests. However, the results indicate that the null hypothesis supporting joint significance of covariates in the PSM model is rejected at 1 percent, after matching, whereas it was never rejected before matching (See Table 4 in Appendices). The rejection of the null hypothesis indicates that the balancing test is satisfied and the specification of the propensity score is fairly successful in terms of balancing the distribution of covariates between the two groups.

Impact Estimation Using Double Difference Method

The Double Difference model was used to estimate the impact[4] of the Cotton YIELD Programme on real crop income which is the second objective of this study. The results from the estimated DD model are reported in Table 5 in Appendices. The dependent variable used in the DD model was log real crop income per hectare and independent variables included were participation dummy (p2014), year dummy (year) and a product of

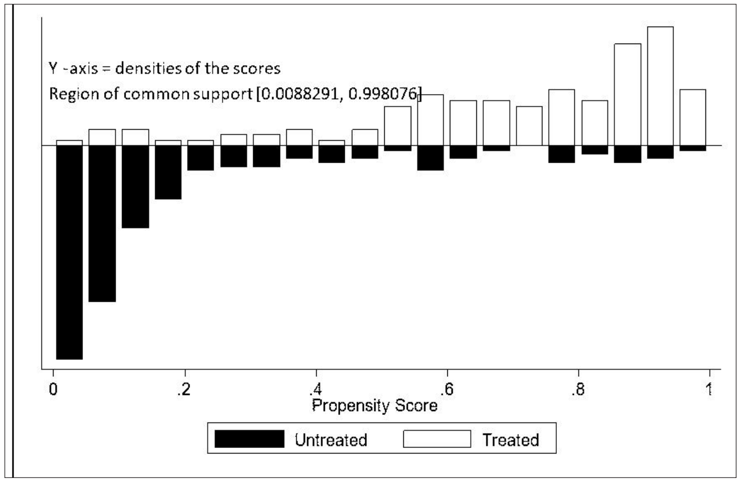

Fig. 1. Propensity score distribution and region of common support (1)

Source: Author

participation and year dummies (p2014*year) among others. Log real crop income was used for easy interpretation of results (Wooldridge, 2013). The results show that the R^2 is 0.47 and the model is statistically significant at 1 percent, 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 crop net income per hectare. In contrast to results in Table 2 in Appendices, the results in Table 5 in Appendices show no statistically significant difference in the percentage of mean crop income per hectare of participants and non-participants without the programme (See coefficient of 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). Furthermore, the results in Table 5 in Appendices indicates that with the programme, the mean income per hectare for participants and non-participants had increased to 60.60 percent (coefficients of p2014 + year + p2014*year + constant) and 25 percent (coefficients of year + constant) respectively and the difference is statistically significant at 1 percent. These results suggest a growth in mean income of the non-participants of 2.3 percent. That is from 22.70 percent (Coefficient of year + constant) without the programme to 25 percent (coefficient of a constant) with the programme. 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 income (Ravallion 2001).

A comparison of the real crop income of the Cotton YIELD Programme participants and non-participants (Table 5 in Appendices) shows that the Cotton YIELD Programme has significantly increased income per hectare of participants by 38.10 percent, as represented by the coefficient of p2014*year. The positive and significant impact of the Cotton YIELD Programme on smallholder cotton farmers' crop 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 World Bank (2016), Davis et al. (2012) and Asfaw et al. (2006) on the effects of improved agriculture technology on farm household incomes. These studies showed that adoption of improved 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.

CONCLUSION

The overall conclusion of this study is that the Cotton YIELD Programme has significantly increased the crop income of the participants by 38.1 percent, as reported in Table 5 in Appendices. In addition, the study also found that years of education, farm size, membership of local farmer organizations, 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. 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 incomes. Nevertheless, participating in the Cotton YIELD Programme is mainly constrained by distances to extension agents and market outlets. Owing to this, policy interventions that address this constraint could accelerate participation in the Cotton YIELD Programme and consequently increase agricultural income.

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 income. Therefore, this study firstly, 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 so as to improve the spread and intensity of participation in the Cotton YIELD Programme. 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.

NOTES

1. 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).
2. Densities of the scores is defined as the extent of coverage of the scores (Kassie et al. 2011).
3. The p-score command of STATA was used to estimate the region of common support. For details, see Khandker et al. (2010).
4. The term impact is used interchangeably with average treatment effect on the treated in this paper.
5. 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.

REFERENCES

Asfaw S, Shiferaw B 2010. Agricultural Technology Adoption and Rural Poverty: Application of an Endogenous Switching Regression for Selected East African Countries. *Pap*er 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, 19-23 September.

Baker J 2000. *Evaluating the Impact of Development Projects on Poverty.* World Bank, Washington DC.

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

Davis K, Nkonya E, Tato E, Mekonnen DA, 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.

DZL 2015. Improving Smallholder Cotton Yields in Zambia: YIELD/ Cotton Made in Africa Programme, Lusaka Zambia. Presentation. From <http/www.slidesserve.com/dyllis/ yield.> (Retrieved on 10 March 2015).

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.

Green R, Alston JM 1990. Elasticities in AIDS models. *American Journal of Agricultural Economics,* 72: 442-445.

Haggblade S, Kabwe S, Plerhoples C 2011. Productivity Impact of Conservation Farming on Smallholder Cotton Farmers in Zambia. *FSRP, Working Paper Number* 47. Lusaka, Zambia: Food Security Research Project.

Hardaker JB, Huirne RBM, Anderson JR, Lien G 2004. *Coping With Risk in Agriculture.* 2nd Edition. New York: CAB International (Abbr. FMA).

Hassan RM 2015. *Sampling Procedures and Survey Design. Teaching Notes for Part 2.* South Africa: Department of Agricultural Economics, University of Pretoria.

Kassie M, Shiferaw B, Geoffrey M 2011. *Agricultural Technology, Crop Income, and Poverty Alleviation in Uganda.* World Development, Elsevier, 39(10): 1784-1795.

Khandker SR, Koolwal GB, Samad H 2010. *Handbook on Impact Evaluation Quantitative Methods and Practices.* The World Bank, Washington DC.

Manda J, Alene AD, Gardebroek C, Kassie M, Tembo G 2016. Adoption and impacts of sustainable agricultural practices on maize yields and incomes: Evidence from rural Zambia. *Journal of Agricultural Economics,* 67(1): 30- 153.

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

MNDP- Ministry of National Development Planning 2020. *Zambia Sustainable Development Goals Voluntary National Review 2020 Report.*

Ng'ombe J 2013. *Impact of Conservation Farming on Smallholder Farm Households' Income in Zambia: Evidence Using an Endogenous Switching Regression Model*. MSc Thesis. Zambia: University of Zambia.

Nyanga PH, Johnsen FH, Aune JB, Kalinda TH 2011. Smallholder farmers: Perceptions of climate change and conservation agriculture: Evidence from Zambia. *Journal of Sustainable Development,* 4(4): 73-85.

Ogada JM, 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.

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, 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. USA: Texas A and M University.

Tschirley D, Kabwe S 2009. Cotton Sector of Zambia, FSRP African Region, *Working Paper No.* 124. Lusaka, Zambia: Food Security Research Project.

Wooldridge JM 2013. *Introductory Econometrics: Modern Approach.* 5th Edition. USA: Michigan State University.

World Bank 2019. *Accelerating Poverty Reduction in Africa 2019.* Washington DC, USA.

World Bank 2018. *Increasing Agricultural Resilience through Better Risk Management in Zambia.* Washington DC, USA.

World Bank 2014. *Access to Finance for Smallholder Farmers Learning from the Experiences of Microfinance Institutions in Latin America*. Washington DC, USA.

Paper received for publication in August, 2019
Paper accepted for publication in September, 2020

APPENDICES

Table 1: Descriptive characteristics of participants and non-participants of cotton yield programme

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 o (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 (1=married, 0=otherwise)	0.08	0.19	-0.11***
Family size	5.80	6.02	-0.22
Wealth Variables and Farm Characteristics			
Farm size (ha)	2.75	1.09	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 organization (1=yes, 0=otherwise)	0.87	0.42	0.45***

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

Table 2: 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			
Real Crop income (ZMK)/Ha	1, 813.40	806.39	1,007.01***

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

Table 3: Probit estimates of respondents' probability of participation in yield

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)	-0.01 (0.01)	-0.00
Gender of the decision maker (1=male, 0=otherwise)	-0.20 (0.20)	-0.04
Education level of the decision maker (years)	0.34 (0.17)**	0.01
Marital status of the decision maker (1=single, 0=otherwise)	-0.64 (0.32)**	-0.14
Family size	-0.07	-0.02
Wealth and Farm Characteristics	(0.46)	
Land cultivated (ha)	0.06 (0.15)	0.01
Farm size (ha)	0.12 (0.04)***	0.03

Active family labour (Adult equivalents)	0.20 (0.06)***	0.05
Own animal traction (1=yes, 0=otherwise)	0.81 (0.21)**	0.17
Off farm Income (1=yes, 0=otherwise)	-0.03 (0.02)	-0.06
Assets value (ZMK00)	0.02 (0.01)**	0.03
Institutional and Access Related Factors		
Distance to local markets (km)	-0.11 (0.04)***	-0.02
Distance to extension agents (km)	-0.31 (0.89)***	-0.07
Access to credit (1=yes, 0=otherwise)	0.73 (0.23)***	0.15
Membership to farmer organization (1=yes, 0=otherwise)	0.86 (0.20)***	0.18
Constant	-0.52 (0.67)	
Number of observations	300	
Log likelihood	-114.99	
LR Chi2 (15)	92.4	
Pro>chi2	0.00	
Pseudo R2	0.44	

* 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

Table 4: 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 (1=male, 0=otherwise)	0.57	0.67	0.092*
Level of education level in years	6.39.	5.92	0.300
Marital status (1=married, 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

Table 5: Double difference estimates of programme impact on real crop income 2015

Variable	*Coefficients*
Dependent Variable Log Real Crop Net Income per hectare[1] Independent Variables	
P2014 (1=participant and 0= Otherwise)	-0.03 (0.10)
Year (1=follow-up and 0=Otherwise)	0.02 (0.09
P2014*year (impact estimate)	0.381 (0.15)***
Age Decision Maker (years)	-0.00 (0.00)
Gender (1=male, 0=otherwise)	0.03 (0.07)
Education level of the Decision Maker (years)	0.05 (0.01)***
Marital status of the Decision Maker (1=single, 0=otherwise)	-0.11 (0.06)*
Family size	-0.01 (0.02)
Labour (Adult equivalents)	0.03 (0.00)***
Land cultivated	0.02 (0.04)
Farm size (hectares)	0.03 (0.01)**
Own animal traction (1=yes, 0=otherwise)	0.22 (0.08)***
Access to off-farm income (1=yes, 0=otherwise)	-0.1 (0.67)
Log Assets value in ZMK	0.09 (0.04)***
Distance to local markets (km)	-0.07 (0.07)**
Distance to extension agents (km)	-0.33 (0.04)***
Access to loans/credit (1=yes, 0=otherwise)	0.08 (0.10)
Membership to farmer organisation (1=yes, 0=otherwise)	0.17 (0.07)**
Constant	0.23 (0.22)
Number of observations	258
F (18, 239)	9.30
Prob > F	0.00
R-squared	0.47

*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