The impact of conservation agriculture adoption on farmer welfare: a comparative assessment of Zambia and Zimbabwe

by

Nashon Ngalande

A dissertation submitted in partial fulfilment of the requirements of the degree

MSc Agric (Agricultural Economics)

in the

Department of Agricultural Economics, Extension and Rural Development

Faculty of Natural and Agricultural Sciences

University of Pretoria

Pretoria

4th May 2021

DECLARATION OF ORIGINALITY

I, Nashon Ngalande, declare that the dissertation, which I hereby submit for the degree Master of Science in Agriculture (Agricultural Economics) at the University of Pretoria, is my own work and has not previously been submitted by me for a degree at this or any other tertiary institution.

Signature:

Date: 4th May 2021

DEDICATION

I dedicate this dissertation to God Almighty for giving me the strength to accomplish this degree.

ACKNOWLEDGEMENT

I thank my supervisor, Professor Eric Mungatana, for his academic, motivational, and emotional support during my university study and during this dissertation. I appreciate the Mastercard Foundation Scholarship for the substantial financial support throughout my study. I would also like to thank the African Conservation Tillage Network (ACT) for collecting and availing of the data used in this study. In turn, ACT acknowledges the partnership and financial support from the Common Market for Eastern & Southern Africa (COMESA). ACT are also grateful to various public and private partners in Zambia and Zimbabwe for their support in the fieldwork. The key role played by the country coordinators Herbert Mwanza and Jeffrey Jinya in Zambia and Zimbabwe is acknowledged. Special thanks to the District enumerators Maurice Mapani (Mumbwa – Zambia), Malama Charles (Mpongwe – Zambia), Chinyise Tiniel (Shamva – Zimbabwe) and Memory Jani (Mutoko-Zimbabwe). ACT also acknowledges the willingness of the key informants and smallholder farmers for agreeing to be interviewed.

The impact of conservation agriculture adoption on farmer welfare: a comparative assessment of Zambia and Zimbabwe

by

Nashon Ngalande

Degree: MScAgric (Agricultural Economics)

Department: Agricultural Economics, Extension and Rural Development

Supervisor: Prof. Eric Dada Mungatana

ABSTRACT

A comprehensive study on the impact of conservation agriculture on farmer welfare has largely remained empirically untested in Africa. Where the impact of conservation agriculture has been estimated, essential non-monetary services such as food security, soil health, social cohesion, gender disparities, resilience to drought, adaptation to climate change and environmental sustainability have not been studied together. In addition, no study compares the adoption and impact of CA between Zimbabwe and Zambia. This study uses pooled cross-sectional data from 279 project and 127 non-project participants drawn from Zambia and Zimbabwe to test whether conservation agriculture (CA) causally improves smallholder farmer welfare. We estimated the propensity score matching model using the nearest neighbour, stratification and kernel matching algorithms to determine the causal impact of conservation agriculture on farmer welfare. The results show that CA has statistically significant causal impact on increasing total agricultural yield (t=6.332, p=0.000), maize yield (t=4.806, p=0.000), resilience to drought (t=7.102, p=0.000), adaptation to climate change impacts (t=6.496, p=0.000), number of meals per day (t=5.103, p=0.000), food security (t=3.639, p=0.000), household income (t=1.694, p=0.10), accumulation of productive assets (t=2.338, p=0.05), ability to address agricultural calendar bottlenecks (t=6.123, p=0.000), increasing production costs (t=2.639, p=0.01), addressing gender disparities (t=5.743, p=0.000), improving soil health (t=6.581, p=0.000) and reducing the amount of forest area cleared per year (t=2.951, p=0.01). However, CA had no statistically significant impact on the number of food-insecure months and social cohesion. We observe that Zimbabwe farmers have access to 2.7 meals per day compared to Zambia's 2.9 meals per day. It shows that conservation agriculture has had more impact in Zambia than in Zimbabwe. Since the cross-country analysis shows that farmers in Zimbabwe are more likely to adopt CA, policy in Zambia could similarly increase adoption rates by focussing on promoting the technology among older farmers, especially those who perceive soil fertility as low. This study shows that CA improves the welfare of smallholder farmers through improved agronomic, food security, economic, social and environmental benefits that it offers. Therefore, the results point to the need to promote extension services to build capacity among farmers, improve markets for inputs such as jab planters and Chaka hoes (CA specialised weeding hoes), and introduce and train farmers on the use of herbicides to reduce labour demands. Agriculture extension remains the most reliable source of information on better production methods and agricultural practices, including labour saving and production intensification.

Keywords: Conservation agriculture, propensity score matching, welfare outcomes, Zambia, Zimbabwe.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF ACRONYMS

ACT	African Conservation Tillage Network
CA	Conservation Agriculture
CFU	Conservation Farming Unit
CIA	Conditional independence assumption
COMESA	Common Market for Eastern and Southern Africa
FAO	Food and Agriculture Organisation
KM	Kernel matching
LR	Likelihood ratio
NGOs	Non-governmental organisations
NN	Nearest neighbour
PS	Propensity score
PSM	Propensity score matching
SADC	Southern African Development Community
USA	United States of America

CHAPTER 1: INTRODUCTION

1.1 Introduction and background

This paper uses a comparative approach to assess the impacts of conservation agriculture (CA) adoption on the welfare of smallholder farmers in Zambia and Zimbabwe. CA is a farming system based on three principles: minimum mechanical soil disturbance, permanent soil organic cover, and species diversification grown in rotations or associations (Food and Agriculture Organization, 2021). Minimum mechanical soil disturbance involves direct seeding through unploughed soil covered with stubble or cover crops, e.g. planting in hand hoe dug basins (Haggblade and Tembo, 2003) or using hand, animal or tractor no-till planters. Soil organic cover is a practice where cover crops are grown, or crop residues from previous harvests are retained on the soil surface (Corbeels et al., 2014). Species diversification includes the rotation of legumes with cereal crops or intercropping on the same plots to recycle soil nutrients leached to deeper layers and increase nitrogen fixation (Milder et al., 2011). Relative to conventional tillage, CA offers a unique dynamic to the agriculture sector: it leads to optimum crop yields and profits (Rockström et al., 2009; Ngwira et al., 2013) and achieves balanced agricultural, economic, nutritional, social and environmental benefits (Dumanski et al., 2006). The combined pool of benefits from production, the environment and reduced input use provided by CA is more crucial than production alone (Dumanski et al., 2006).

Government policies play a vital role in enhancing technology adoption and intensification. For example, in Zambia, the Sixth National Development Plan contains an overall Agriculture Policy that aims to facilitate and support a sustainable and competitive agricultural sector that assures food security at national and household levels and maximises the sector's contribution to Gross Domestic Product (GDP). Since independence, the Zambian government has provided agricultural subsidies in the form of improved seed and fertiliser, enabling many smallholder farmers to access farm inputs. These policies have been intended to improve productivity, reduce soil nutrient depletion, soil erosion and encroachment of agriculture into marginal lands. This implies improvement in natural resource availability in the form of sinks for climate change mitigation and adaptation and improved resilience of the agro-ecosystem to climate variability (Shula et al., 2012). The agriculture policy in Zimbabwe seeks to assure national and household food and nutrition security, ensure that the existing agricultural resource base is maintained and improved, generate income and employment to feasible optimum levels, and increase agriculture's contribution to the Gross Domestic Product (GDP). In order to make agriculture more productive and sustainable, the Zimbabwe Government plans to increase crop productivity and production through the following strategies: provision of subsidised inputs, development of high yielding and drought-tolerant crop varieties to promote sustainable agricultural production, including conservation agriculture techniques (see http://faolex.fao.org/docs/pdf/zim149663.pdf). In both countries, the agriculture policy focuses on sustainably increasing production and productivity and supporting resource-poor farmers through subsidised inputs to increase access to fertiliser and seeds for staple crop production. In addition, the policies seek to facilitate the transition from conventional farming and promote adaptation to the effects of climate through the adoption of modern farming technologies such as conservation agriculture.

CA has been promoted in Zambia since the mid-1980s by the government and Non-governmental organisations (NGOs), with funding from development partners such as the Swedish International Development Agency, which funded the soil conservation and fertility project in 1985 (Baudron et al., 2007). Prominent organisations include the Conservation Farming Unit (CFU) of the Zambia National Farmers Union, the Golden Valley Agricultural Research Trust in Zambia, the Zambian Ministry of Agriculture and Cooperatives and the Institute of Agricultural and Environmental Engineering project. By the year 2000, promoting CA adoption became a national agricultural policy target in Zambia (Haggblade and Tembo, 2003). Despite these efforts and investments, many studies show that CA adoption rates in Zambia is not consistent with the investments made. Arslan et al. (2014) reported a 13 per cent adoption rate for minimum tillage in 2004, which decreased to 5 per cent by 2008. Grabowski et al. (2014) observed an adoption rate of 13 per cent of minimum tillage for cotton farmers in 2011. Ngoma et al. (2014) reported an adoption rate of 3.55 per cent for planting basins in 2010, which slightly increased to 3.88 per cent by 2012. Kuntashula et al. (2014) observed an adoption rate of 12 per cent for minimum tillage and 19 per cent for crop rotation in 2012. Simasiku et al. (2010) attributes the inconsistent adoption rates to the inconsistency of programmes by major NGOs, inadequate training by the technology implementers, incomprehension of the impacts and poor delivery of inputs.

While empirical work on CA's impact in Zambia exists, there exist inconsistencies in the nature and direction of this impact. Haggblade and Tembo (2003), Ngoma et al. (2014), Abdulai (2016), Ng'ombe et al. (2017), and Mango et al. (2020) report that CA leads to welfare gains through increased crop yields, household incomes, soil fertility, and food security. However, Haggblade and Tembo (2003) reported that hand-hoe based CA is labour intensive, especially in the early adoption years, while Nyanga et al. (2012) showed that CA might increase or decrease women's labour requirements. Kuntashula et al. (2014) reported that crop rotation had no significant effect on household income, while (Arslan et al., 2015) found no significant impact on maize yield from the adoption of minimum soil disturbance and nitrogen fixing crop rotation in Zambia.

CA has been promoted and evaluated at a limited scale among smallholder farmers in Zimbabwe since the early 1980s (Haggblade and Tembo, 2003; Andersson and Giller, 2012). However, Zimbabwe's economic crisis in the 1990s led to drastic declines in government support for agriculture, implying deepening rural poverty and food insecurity. This led to large-scale CA promotion as part of the donor-funded farmer relief and support programmes in 2003 (Andersson and Giller, 2012), by institutions such as River of Life Church, UK's Department for International Development, International Crops Research Institute for the Semi-arid Tropics, and International Maize and Wheat Improvement Centre (Mazvimavi, 2010). However, the rates of CA adoption in Zimbabwe is not consistent with the investments made and the expectation (Mazvimavi, 2010; Derpsch et al., 2010). In 2009, Kassam et al. (2009) reported a CA adoption rate of 0.4 per cent of the 2008/09 crop area, while Marongwe et al. (2011) reported that CA was practised on 15,000 ha (about 1 per cent of the total area dedicated to cereal production) in 2009. Mazvimavi and Twomlow (2009) observed that 30 per cent of their respondents practised crop rotation between 2004 and 2007. Mazvimavi et al. (2010) reported 56 per cent of farmers retaining residues in the 15 districts in 2009, while Pedzisa et al. (2015) observed a 22.5 per cent adoption of crop rotation, 81.9 per cent adoption of planting basins, and a 32.5 per cent adoption of mulching between 2008 and 2011. The inconsistent adoption rates have been attributed to limited access to legume seeds required for rotations, limited information on the benefits of CA, withdrawal of NGOs after a few years of input support, competition for crop residues in mixed crop-livestock systems, limited access to credit, and inappropriate soil fertility management systems (Mazvimavi et al., 2010; Mazvimavi, 2010; Marongwe et al., 2011).

Evidence of CA impacts on farmers' welfare in Zimbabwe also remains inconsistent. Twomlow et al. (2008), Mazvimavi et al. (2008), Thierfelder et al. (2012), and Ndlovu et al. (2014) report positive impacts on crop yields, soil fertility, gross margins and food security. However, Nyamangara et al. (2013) observed that mulching, crop rotation and mulching + crop rotation decreases crop yields when implemented without mineral fertiliser, while Corbeels et al. (2014) observed that CA's impact on farm income is not immediate and is far less evident on some farms. Mupangwa et al. (2017) observed no CA superiority over conventional tillage, while Giller et al. (2009) reported that the empirical evidence on CA's benefits is variable and unclear. Further, Baudron et al. (2011) observed that CA recorded lower cotton yield compared to conventional tillage practice while Mazvimavi and Twomlow (2009) observed that CA's basin system has a higher cost of maize production compared to the conventional draft tillage system.

It follows from the above that CA adoption rates in the two southern African countries are not consistent with investments in its promotion and intensification, with the relative adoption rates for some CA technologies being higher in Zimbabwe. These contradictory cross-country findings on adoption rates, experiences, and impacts warrant further investigation. We contribute to the existing literature on the impact of CA adoption in the following ways: we investigate comprehensively, for the first time, the impact of CA by extending the analysis to essential non-monetary services such as food security, soil health, social cohesion, gender disparities, resilience to drought, adaptation to climate change and environmental sustainability. To the best of the authors' knowledge, no study compares the adoption and impact of CA between Zimbabwe and Zambia. A cross-country comparison can potentially provide policymakers the opportunity to analyse CA impacts across diverse environments since several studies base their evidence on localised cross-sectional surveys (Hobbs, 2007). Evidence from such cross-country comparisons can facilitate lesson sharing and sensitise the agricultural development community on the demerits of broad generalisation regarding CA's impact (Mazvimavi et al., 2010). Such evidence will also provide for the external validity of CA adoption benefits by filling a knowledge gap concerning the need to analyse CA's impact beyond a single project or country.

Consequently, this paper uses a comparative approach to assess the impacts of CA adoption on smallholder farmers' welfare in Zambia and Zimbabwe. We will initially determine the impacts of CA adoption on different welfare outcomes using a quasi-experiment, then use experiences from Zambia and Zimbabwe to draw cross-country policy lessons.

CHAPTER 2: METHODOLOGY

2.1 Study area and data sources

The data comes from the African Conservation Tillage Network (ACT), which has been promoting CA in Eastern, Southern and West Africa for the past 20 years. From its base in Harare (1998-2005) and thereafter from the Nairobi Kenya base, ACT has supported CA development in all the SADC countries. The specific activities ACT promotes in these countries are (a) capacity building of farmers, extension workers and research officers through training, (b) support to government and NGO CA extension programmes, (c) CA stakeholders' networking, knowledge management and information sharing. In this context, ACT has been collaborating with different stakeholders implementing CA programmes on the ground. They include Ministries of Agriculture in Zambia and Zimbabwe, Gwebi college of agriculture, University of Zimbabwe, NGOs (e.g., CFU Zambia), and regional economic communities, namely SADC and COMESA. The survey data used in this study were collected under a COMESA project with the groundwork implemented by various partners. In Zambia, data were collected from CA projects in Central province (Mumbwa District) and Copperbelt province (Mpongwe District). In Zimbabwe, data were collected from CA projects in the provinces of Mashonaland East (Mutoko District), and Mashonaland Central (Shamva District). To measure the impact of CA on farmer welfare, ACT collected data from 279 project and 127 non-project participants in Zambia and Zimbabwe on the outcomes defined in Table 2.1. The sample was such that the ACT farmers were already exposed to CA technology as they have been interacting with ACT staff for over 20 years and were practicing some of the CA techniques, including minimum mechanical soil disturbance, permanent soil organic cover and crop diversification and rotation, while the control group had no exposure to CA technology as they had no prior interaction with ACT staff.

Table 2.1: Outcome variables used to measure welfare impact

Outcome variable	Definition
Country of residence	Dummy=1 if country is Zimbabwe, 0 if Zambia
Total agricultural yield	Dummy=1 if total agricultural yield increased, 0 otherwise
Total maize production	Dummy=1 if total maize production increased, 0 otherwise
Resilience to drought	Dummy=1 if resilience to drought increased, 0 otherwise
Adaptation to climate change	Dummy=1 if adaptation to climate change is enhanced, 0 otherwise
Number of meals per day	Continuous
Number of food-insecure months	Continuous
Food security	Dummy=1 if food security improved, 0 otherwise
Household income	Dummy=1 if household income increased, 0 otherwise
Accumulation of productive assets	Dummy=1 if ability to accumulate productive assets increased, 0 otherwise
Addressing agricultural calendar bottlenecks	Dummy=1 if ability to address agricultural calendar bottlenecks increased, 0 otherwise
Total agricultural production costs	Dummy=1 if total agricultural production costs increased, 0 otherwise
Social cohesion	Dummy=1 if social cohesion enhanced, 0 otherwise
Gender disparities	Dummy=1 if gender disparities reduced, 0 otherwise
Soil health	Dummy=1 if soil health improved, 0 otherwise
Forest area cleared per year	Dummy=1 if forest area cleared per year decreased, 0 otherwise

The analysis is thus based on a pooled cross-sectional household sample of 406 smallholder farmers. In Zambia, ACT used multistage sampling to choose lower-level sampling classes: wards and villages. The two regions (districts) were assigned 102 households each. ACT made efforts to ensure the representativeness of the sample depending on the population of the sampling units. Proportionate random sampling was used to select wards from each district, villages from each ward and the number of households from each village. The sampling procedure was similar for Zimbabwe, where 101 households from Mutoko and another 101 households from Shamva districts were sampled. In both countries, data were collected using semi-structured questionnaires that covered issues on empowerment, adoption of technologies, the overall impact of technologies, access to resources, labour and gender, among others.

2.2 Analytical framework and estimation techniques

This study defined CA adoption as having a portion of land dedicated to at least two of the CA principles, one of them being no-till farming. Conservation agriculture adoption is among many efforts a farmer implements to maximise the farm's overall utility or profit. More often than not, the maximisation of expected utility subject to available land, credit access, farm labour, risk attitudes, and other constraints, including lack of appropriate CA equipment, derive the farmer's decisions during a given time (Feder et al., 1985; Marenya and Barrett, 2007; Kassie et al., 2015). We considered the expected utility or expected profit as a function of the farmer's choice of crops and the discrete choice of adopting CA in a given period. Feder et al. (1985) explain the modelling of a farmer who seeks to maximise utility or profit from increased income, yield, soil health and other benefits of adopting technology like CA.

Although the adoption of CA is expected to lead to positive outcomes, estimating such outcomes in observational research is an arduous task due to the difficulty of observing counterfactuals (Rubin, 1974; Blundell and Costa Dias, 2000). The non-randomised assignment to the treatment group leads to biased outcomes because the treated and control groups' results are different even in the absence of treatment (Caliendo and Kopeinig, 2008). The adoption of CA, for instance, is not randomly assigned to the treatment (adopters) as they can decide to adopt or otherwise based on unobservable characteristics such as farming experience and access to information. In other circumstances, technology adoption can result from a funded project or government policy that incentivises the farmers. As a result, we follow a potential outcome framework for causal inference given by Rubin (1974) to estimate the causal effect of adopting CA on a set of outcome variables. Stated differently, we estimate the Average Treatment Effect on the Treated (ATT) on farmer welfare outcomes. Several studies have relied on the propensity score matching (PSM) techniques to evaluate the impact of modern farming technologies and adoption methods (Ng'ombe et al., 2014; Kuntashula and Mungatana, 2015; Mango et al., 2020). This study uses conservation agriculture adoption as the treatment variable, while the outcome variables are discussed in Table 2.1.

According to Rubin (1974), the outcome framework to estimate the ATT is given as follows:

$$E(Y_1 - Y_0 | T = 1) \tag{1}$$

Where; E denotes the expected difference in the outcome $(Y_1 - Y_0)$ between the treatment and the counterfactual, i.e., between adopting CA, $T = 1$ and had CA not been adopted, $T = 0$.

Two assumptions are needed to validate the matching methods. The first assumption is called the conditional independence assumption (CIA), which states, given a set of observable covariates X, the potential outcome in case of no treatment (Y_0) is independent of treatment assignment (T), as illustrated below.

$$Y_0 \coprod T \backslash (X) \tag{2}$$

The second assumption is that of common support or the overlap condition, which requires units with similar characteristics in the treatment and comparison group. It entails matching units from the treatment and controls with a similar propensity score. In this case, we ignore all control units that do not share a propensity score with the treatment within the common support region. The above two assumptions ensure that within each cell defined by X, treatment assignment, is random. The outcome of control households can be used to estimate the counterfactual effect of the treated in the case of no treatment.

It is better to use many observable characteristics to match truly similar units. However, suppose the matching variables' list is too long, too detailed, or contains exceptional values. In that case, it can be challenging to find two units with the same characteristics in the treatment and comparison group. The larger the number of variables for matching, the more difficult it is to find a good match. To overcome the curse of dimensionality, Rosenbaum and Rubin (1983) showed that matching on a single continuous variable, the propensity score (PS), rather than matching on a multidimensional covariate vector, is possible. Heckman et al. (1998) define a propensity score as the conditional probability of participation or in our study of adopting CA and is mathematically expressed as:

$$P(X_i) = \Pr(T = 1|X_i) \tag{3}$$

which is the probability an individual *(i)* chooses *(T)* given their covariates.

The propensity score is generally unknown. This study estimated it using a probit regression where the dependent or treatment variable equalled one if the household had a portion of land dedicated to at least two of the CA principles, one of them being no-till farming and zero otherwise, as expressed in equation (4) below.

$$\text{PCAadopt} = \beta_0 + \beta_1\text{country} + \beta_2\text{age} + \beta_3\text{educ} + \beta_4\text{married} + \beta_5\text{mixedfarm} + \beta_6\text{inputs} + \beta_7\text{farmsize} + \beta_8\text{soil} + \beta_9\text{extension} + \beta_{10}\text{group} + \beta_{11}\text{offarm} + \beta_{12}\text{credit} \quad (4)$$

We then checked for the balancing property of the propensity scores to ensure the treatment and control observations have the same distribution of propensity scores within the region of common support (Beal and Kupzyk, 2014). Following Brookhart et al. (2006), we included variables that were correlated with the outcome variables and the treatment or only correlated with the outcome variables in the propensity score estimation. We then picked a robust probit model that satisfied the balancing property within the region of common support, as shown in equation (4). Our data have several dummy explanatory variables, which may lead to perfect collinearity. We chose the base group for each category to avoid the dummy variable trap and used only one dummy variable.

We implemented the matching procedure using three matching algorithms to ensure the robustness of the estimates. Firstly, we used the nearest neighbour (NN) matching, where the individual from the control group is chosen as a matching partner for a treated individual closest to the propensity score. We implemented NN with replacement, where an individual can be used more than once as a match. NN with replacement allows an increase in the average quality of matches and a decrease in bias (Caliendo and Kopeinig, 2008). Secondly, we implemented a stratification and interval matching technique. Stratification matching partitions the region of common support of the propensity score into intervals or strata and calculates each interval's impact by taking the mean difference in outcomes between treated and control observations. The use of intervals (strata) under normality removes most of the covariates' bias (Caliendo and Kopeinig, 2008).

Thirdly, while NN and stratification matching techniques use only a few observations from the comparison group to construct a treated individual's counterfactual outcome, Kernel matching (KM) is a non-parametric matching estimator. KM uses weighted averages of all units in the comparison group to construct the counterfactual outcome (Smith and Todd, 2005; Caliendo and Kopeinig, 2008). Consequently, KM has a lower variance because it uses more information. However, KM has the possibility of using bad matches. Thus, Caliendo and Kopeinig (2008) emphasised the importance of proper imposition of the common support condition.

To make cross-country lessons for CA adoption, we initially assessed whether farmers drawn from Zambia and Zimbabwe systematically differ in variables hypothesised to determine the probability of CA adoption. We thus proceeded to test whether country of residence had the same effect on the probability for CA adoption as the individual independent variables included in equation (4). Using HH head age to illustrate the general testing approach, we followed Wooldridge (2013) to include a HH head age and country of residence interaction term ($age + country$) in the equation that predicts the probability of CA adoption (see equation (5)).

$$\begin{aligned} \mathrm{CA} = {} & \beta_0 + \beta_1 \mathrm{country} + \beta_2(\mathrm{age} + \mathrm{country}) + \beta_3 \mathrm{educ} + \beta_4 \mathrm{married} + \\ & \beta_5 \mathrm{mixedfarm} + \beta_6 \mathrm{inputs} + \beta_7 \mathrm{farmsize} + \beta_8 \mathrm{soil} + \beta_9 \mathrm{extension} + \\ & \beta_{10} \mathrm{group} + \beta_{11} \mathrm{offarm} + \beta_{12} \mathrm{credit} \end{aligned} \tag{5}$$

We expect $\beta_1 = 0$ under the null hypothesis, otherwise we would conclude that country of residence and HH head age have differential impacts on the probability of CA adoption.

CHAPTER 3: RESULTS AND DISCUSSIONS

3.1 Impacts of CA adoption on farmer welfare

According to Rosenbaum and Rubin (1983), the first step in an impact assessment study is to establish whether there exist systematic pre-treatment differences between the treated and controls, to the extent that determination of causation becomes difficult. Table 3.3 explores statistics from t-tests and pairwise comparisons that characterise CA adopters and non-adopters across selected attributes for Zimbabwe while Table 3.2 presents the same analysis for Zambia and Table 3.3 shows the results for the pooled data set.

Table 3.1: Characteristics of households by treatment for Zimbabwe

Variable	Adopters	Non-adopters	t-stat	P>|z|
Household demographic characteristics				
Age of HH head	54	49.46	-1.969	0.050*
Maximum level of education of HH head	9.03	9.43	0.595	0.553
HH head is married	68.49	73.21	0.652	0.515
Plot characteristics				
Practice mixed farming	76.03	76.79	0.113	0.910
Inputs obtained outside the HH	6.16	1.79	-1.283	0.201
Farm size	1.37	1.73	1.986	0.048
Perception of soil fertility before CA adoption	78.08	23.21	-8.348	0.000***
Access to information, institutional services, and social capital				
Agricultural extension	56.16	30.36	-3.359	0.001***
Belonging to a farmer group	45.21	25.0	-2.661	0.008***
Off-farm income	91.78	85.71	-1.292	0.198
Credit access	5.48	0.00	-1.793	0.075*

** Significant at 10%, ** significant at 5%, *** significant at 1%. Source: survey data*

Table 3.2: Characteristics of households by treatment for Zambia

Variable	Adopters	Non-adopters	t-stat	P>|z|
Household demographic characteristics				
Age of HH head	52.36	42.20	-5.120	0.000***
Maximum level of education of HH head	9.12	9.32	0.465	0.643
HH head is married	83.46	84.51	0.193	0.847
Plot characteristics				
Practice mixed farming	51.13	26.76	-3.432	0.001***
Inputs obtained outside the HH	87.21	35.21	-9.029	0.000***
Farm size	14.63	8.83	-1.448	0.149
Perception of soil fertility before CA adoption	98.50	18.31	-21.85	0.000***
Access to information, institutional services, and social capital				
Agricultural extension	84.21	1.41	-18.53	0.000***
Belonging to a farmer group	96.24	60.56	-7.394	0.000***
Off-farm income	34.59	63.38	4.080	0.000***
Credit access	9.02	2.82	-1.673	0.096*

** Significant at 10%, ** significant at 5%, *** significant at 1%. Source: survey data*

Table 3.1 above shows that CA adopters in Zimbabwe are likely to be older, perceive their soils to be unfertile before CA adoption, receive extension service from CA promoters, are members of a farming group and have some form of access to credit. From Table 3.2 above, we observe that CA adopters in Zambia are likely to be older than non-adopters, practice mixed farming (crops and livestock), can obtain outside the household inputs, perceive low soil fertility of their soils prior to CA adoption, have access to extension by CA promoters, belong to a farmers group, have access to off-farm income and have some form of access to credit. The descriptive statistics for the pooled data set are presented in Table 3.3 below.

Table 3.3: Characteristics of households by treatment for pooled data

Variable	Adopters	Non-adopters	t-stat	P>|z|
Household demographic characteristics				
Age of HH head	53.22	45.40	-5.14	0.000***
Maximum level of education of HH head	9.07	9.37	0.757	0.449
HH head is married	75.63	79.53	0.389	0.863
Plot characteristics				
Practice mixed farming	64.16	48.82	-2.941	0.004***
Inputs obtained outside the HH	44.80	20.47	-4.825	0.000***
Farm size	7.69	5.70	-0.922	0.357
Perception of soil fertility before CA adoption	87.81	20.47	-17.788	0.000***
Access to information, institutional services, and social capital				
Agricultural extension	69.53	14.17	-12.039	0.000***
Belonging to a farmer group	69.53	44.88	-4.865	0.000***
Off-farm income	0.65	0.73	1.736	0.083*
Credit access	7.17	1.57	-2.318	0.021**

** Significant at 10%, ** significant at 5%, *** significant at 1%. Source: survey data*

Table 3.3 shows that CA adopters in Zambia and Zimbabwe are more likely to be older, derive a lower percentage of their household incomes from off-farm sources, practice mixed farming, belong to farmer groups, use inputs obtained from sources outside the household, access credit, access agricultural extension services, and perceive on-farm soil fertility as low before CA adoption. The significance of age in increasing the likelihood of CA adoption is consistent with the findings of Ng'ombe et al. (2014), who observed that older farmers in Zambia were more likely to adopt CA practices since they have more farming experience and physical capital. Off-farm income, which is essential in meeting the capital costs of implementing new technologies, significantly determines the adoption of crop rotation (a CA practice) in Zambia (Ng’ombe et al., 2017). Although our results show that mixed farming increases the likelihood of adopting CA practices, it also decreases the proportion of maize residue retained as soil mulch and livestock feed (Jaleta et al., 2013). It follows that finding alternative feed sources for livestock and better extension service is crucial in adopting CA for mixed farmers (Jaleta et al., 2013).

Group membership is essential in adopting technologies since it leads to social capital access, which reduces transaction costs and increases bargaining power, eventually enabling farmers to realise higher returns on sales. Social capital also contributes to information exchange, input access and credit access (Mango et al., 2020). The significance of the ability to access inputs from outside the household in CA adoption is consistent with Corbeels et al. (2014), who observed that the availability of suitable input and output markets is a prerequisite for adopting any technology. Besides, inputs sourced from outside, such as hybrid seeds, are essential for yield gains Haggblade and Tembo (2003), income and food security (Khonje et al., 2015). The significance of access to credit (an indicator of liquidity constraint) in determining CA's adoption is consistent with Abdulai (2016), who notes that farmers with no credit access are less likely to adopt technologies. Many researchers, including Mazvimavi and Twomlow (2009), Arslan et al. (2014) and Mango et al. (2020), note the significance of access to extension in CA adoption: it increases access to information on better production methods, practices and CA performance. Finally, the importance of farmer perception of soil fertility before CA adoption is consistent with Abdulai (2016) observation that farmers experiencing low soil fertility are likely to adopt CA to retain soil fertility.

It follows from Table 3.3 that there exist systematic pre-treatment differences between CA adopters and non-adopters in our sample, implying that we could observe significant differences in outcome variables independent of CA. Given the presence of self-selection bias, impact assessment theory recommends that analysts should use statistical procedures to mimic complete randomisation in treatment allocation before impact evaluation (i.e., quasi-experimentation), which in turn requires the conditional independence assumption (CIA). To this effect, we used STATA 15 to estimate the propensity score equation (4) (the propensity score theorem is a corollary of the CIA) and confirmed that the balancing property was satisfied before matching.

The balancing property ensures that treatment assignment is statistically random and that treatments and controls have the same propensity scores distribution within the common support region, implying we can attribute any differences between treatments and controls to CA adoption as shown in the appendices (Appendix A to Appendix C). Table 3.4 presents the results of probit estimation using PSCORE (calliper 0.001) for the pooled dataset. Economic theory, an extensive literature review, data availability, common sense, and considerations of model fit informed the selection of independent variables included in (4). The final model had a region of common support bounded by 0.0485055 and 0.99979806. With a pseudo R2 of

49.58 per cent and Prob>chi2=0.0000, we reject the null hypothesis that the explanatory variables jointly equal zero.

Table 3.4: Propensity score estimation of CA adoption

Adoption of CA (treat)	Coef.	Std. Err.	Z	P>|z|
Household demographic characteristics				
Age of HH head (years)	0.0237***	0.0071	3.33	0.001
Maximum education level of HH head (Years)	0.0396	0.0264	1.50	0.133
HH head is married (1=Yes, 0=No)	-0.2953	0.2262	-1.31	0.192
Plot characteristics				
Being mixed farmer (1=Yes, 0=No)	0.3004	0.1887	1.59	0.111
Inputs obtained outside HH (1=Yes, 0=No)	0.4694*	0.2407	1.95	0.051
Farm size (ha)	-0.0059	0.0051	-1.14	0.253
Soil fertility before CA (1=Low, 0=High)	1.7590***	0.1853	9.49	0.000
Access to information, institutional services, and social capital				
Access to extension (1=Yes, 0=No)	0.9341***	0.2037	4.59	0.000
Belonging to a farmer's group (1=Yes, 0=No)	0.0550	0.2153	0.26	0.798
Off-farm income access (1=Yes, 0=No)	0.1163	0.2217	0.52	0.600
Access to credit (1=Yes, 0=No)	0.6952	0.5261	1.32	0.186
Constant	-2.8421***	0.6900	-4.12	0.000
Observations	406			
LR chi2	250.13			
Prob>chi2	0.0000***			
Pseudo R2	0.4958			
Log-likelihood	-129.1950			

**** Significant at 1%, ** significant at 5%, * significant at 10%. Source: survey data*

For robustness and consistency of estimates, we used three algorithms to implement the matching procedures following the propensity scores generated from Table 3.4: nearest neighbour, stratification, and kernel (Caliendo and Kopeinig (2008). We estimated the average treatment effect on the treated (ATT) for the outcome variables discussed in Table 3.4

Table **3.4**. Table 3.5 presents the causal impact estimates of CA on agronomic outcomes.

Table 3.5: Impact of CA adoption on agronomic outcomes

Matching algorithm	Treated	Control	ATT	Std. Err.	t-stat
Increasing total agricultural yield					
Nearest Neighbour	279	32	0.756	0.119	6.332***
Stratification matching	279	119	0.785	0.085	9.192***
Kernel matching	279	119	0.764	0.088	8.704***
Increasing total maize production					
Nearest Neighbour	279	28	0.642	0.133	4.806***
Stratification matching	279	119	0.660	0.098	6.710***
Kernel matching	279	119	0.649	0.108	6.023***
Increasing resilience to drought					
Nearest Neighbour	279	31	0.701	0.099	7.102***
Stratification matching	279	119	0.738	0.085	8.689***
Kernel matching	279	119	0.710	0.106	6.688***
Enhances adaptation to climate change impacts					
Nearest Neighbour	279	32	0.636	0.098	6.496***
Stratification matching	279	119	0.647	0.086	7.842***
Kernel matching	279	119	0.646	0.110	5.891***

******* *Significant at 1%, ** significant at 5%, * significant at 10%. Source: survey data*

Table 3.5 shows that it is the experience of farmers in Zambia and Zimbabwe that adopting CA has a statistically significant impact on increasing total agricultural yield, total maize production, and resilience to drought. Farmers in Zambia and Zimbabwe also experience that adopting CA has a statistically significant impact on enhancing their ability to adapt to climate change impacts. The positive impact of CA on total agricultural yield is consistent with Nkala et al. (2011), who observed that farmers in Central Mozambique who adopt CA had 0.53 probability points of improving crop productivity. They hypothesised that the practice of early planting could explain the increased crop productivity. The positive and statistically significant impact of CA on maize yield is consistent with the findings of Haggblade and Tembo (2003), Mupangwa et al. (2012), and Abdulai (2016). Abdulai (2016) found that CA adoption increased the expected output per hectare by 79 per cent in Zambia. Mupangwa et al. (2012) reported an increased maize grain yield in Mozambique in seasons of low rainfall when 2-4 tonnes per hectare of mulch cover was applied. Finally, the finding that farmers perceive CA as enhancing adaptation to climate change impacts and enhancing resilience to drought is consistent with Mupangwa et al. (2012), who found that an increase in mulch cover during seasons of below-average rainfall increased maize yields in Mozambique. Table 3.6 presents the impact of CA on food security and nutrition outcomes.

Table 3.6: Impact of CA on food security and nutrition outcomes

Matching algorithm	Treated	Control	ATT	Std. Err.	t-stat
Increasing the number of meals per day					
Nearest Neighbour	279	27	0.713	0.140	5.103***
Stratification matching	279	119	0.668	0.090	7.451***
Kernel matching	279	119	0.621	0.110	5.667***
Increasing the number of food-insecure months					
Nearest Neighbour	279	27	-0.773	0.698	-1.110
Stratification matching	279	119	-0.615	0.448	-1.375
Kernel matching	279	119	-0.662	0.510	-1.299
Increasing food security					
Nearest Neighbour	279	34	0.520	0.143	3.639***
Stratification matching	279	119	0.474	0.116	4.093***
Kernel matching	279	119	0.458	0.129	3.543***

***** Significant at 1%, ** significant at 5%, * significant at 10%. Source: survey data*

Table 3.6 shows that it is the experience of farmers in Zambia and Zimbabwe that adopting CA has a statistically significant impact on increasing the number of meals per day (an indicator of food availability) and food security. The positive impact of CA adoption on the number of meals per day is consistent with Jumbe and Nyambose (2016), who recorded an increase in maize production and meal frequency for CA adopters in Malawi. They attribute the increase in the number of meals per day to the staple maize crop production's significant rise. The positive impact of CA on food security is consistent with Mango et al. (2020), who found that CA increased food security in adopters' households in the Chinyanja triangle (Zambia, Malawi and Mozambique). The positive and significant relationship between CA adoption and the number of meals per day confirms the increase in household food security. Despite recording an increase in the number of meals per day and food security, farmers' experience is that CA did not reduce the number of food-insecure months. This finding could point to post-harvest losses and wastage due to inadequate storage facilities at the household level and attack by storage pests (Hodges et al., 2011; Kimiywe, 2015). Table 3.7 presents the impact of CA on economic outcomes.

Table 3.7: Impact of CA on economic outcomes

Matching algorithm	Treated	Control	ATT	Std. Err.	t-stat
		Increasing household income			
Nearest Neighbour	279	34	0.247	0.146	1.694*
Stratification matching	279	119	0.183	0.100	1.823*
Kernel matching	279	119	0.171	0.102	1.684*
		Increasing the accumulation of productive assets			
Nearest Neighbour	279	34	0.323	0.138	2.338**
Stratification matching	279	119	0.314	0.116	2.714***
Kernel matching	279	119	0.281	0.130	2.164**
		Increasing the ability to address agricultural calendar bottlenecks			
Nearest Neighbour	279	32	0.602	0.098	6.123***
Stratification matching	279	119	0.673	0.069	9.798***
Kernel matching	279	119	0.665	0.100	6.632***
		Increasing the total agricultural production costs			
Nearest Neighbour	279	29	0.189	0.142	1.336
Stratification matching	279	119	0.236	0.090	2.639***
Kernel matching	279	119	0.247	0.100	3.480***

**** Significant at 1%, ** significant at 5%, * significant at 10%. Source: survey data*

Table 3.7 shows that it is the view of farmers in Zambia and Zimbabwe that CA has a statistically significant impact on household income, the ability to accumulate productive assets, address agricultural calendar bottlenecks, and the total agricultural production costs. The weakly significant but positive impact of CA on household income suggests that CA's impact on household income might not be immediate but occurs in the long run (Nkala et al., 2011). Our result also lends credence to Kuntashula et al. (2014), who found that the staple crop's (maize) subsistence nature for smallholder farmers means that most farmers do not sell their produce. This finding could also be attributed to the commensurate increase in production costs such that the net income decreases.

Notably, CA's positive impact on household income is consistent with Ogada et al. (2020) in Kenya, who found that an increase in household income improves the capacity to accumulate productive assets, especially livestock. Farmers in Zambia and Zimbabwe could have also used the output realised from increased productivity and yield to acquire productive assets such as livestock and ox-drawn ploughs and address agricultural calendar bottlenecks such as labour for land preparation and weeding, off-farm income for seed purchases and payments for labour.

The finding of Bassett (1988) in Côte d'Ivoire confirm that farmers can cope with seasonal labour bottlenecks by mobilising daily wage labour and the use of herbicides to save labour, especially during the peak season.

Additionally, CA's positive impact on the total agricultural production costs is consistent with Umar et al. (2011) and Andersson and Giller (2012), who hypothesised that CA increases labour and input requirements. Mazvimavi et al. (2008) also showed that the total agricultural production costs are likely to be higher under CA than conventional tillage due to the high labour demand for digging basins, weeding and residue management in the early years of adoption. Table 3.8 presents the impact of CA on social and gender outcomes.

Table 3.8~~3.8~~: Impact of CA on social and gender outcomes

Matching algorithm	Treated	Control	ATT	Std. Err.	t-stat
		Increasing social cohesion			
Nearest Neighbour	279	33	0.228	0.145	1.569
Stratification matching	279	119	0.194	0.109	1.775*
Kernel matching	279	119	0.134	0.091	1.469
		Reducing gender disparities			
Nearest Neighbour	279	33	0.512	0.089	5.743***
Stratification matching	279	119	0.552	0.088	6.295***
Kernel matching	279	119	0.517	0.118	4.395***

**** Significant at 1%, ** significant at 5%, * significant at 10%. Source: survey data*

Table 3.8 reveals that it is the experience of farmers in Zambia and Zimbabwe that adopting CA has a positive and statistically significant impact on reducing gender disparities. The positive impact of CA on gender is consistent with Nyanga et al. (2012), who showed that CA's adoption leads to a positive effect on gender outcomes in increasing household food security for females in Zambia. Nyanga et al. (2012) showed that CA might increase or decrease labour requirements for women depending on the stage of labour requirement. For instance, CA reduces labour requirements for women during basin digging and herbicide application as men mostly do it; however, women's labour requirements increase during hand weeding. Similarly, Siziba et al. (2019) showed that CA improved gender disparities as it increased food security for female-headed households in Zimbabwe. Table 3.9 presents the impact of CA on environmental outcomes.

Table 3.9: Impact of CA on environmental outcomes

Matching algorithm	Treated	Control	ATT	Std. Err.	t-stat
Improving soil health					
Nearest Neighbour	279	31	0.755	0.115	6.581***
Stratification matching	279	119	0.777	0.086	9.051***
Kernel matching	279	119	0.755	0.112	6.720***
Reducing the forest area cleared per year					
Nearest Neighbour	279	29	0.205	0.128	1.600
Stratification matching	279	119	0.263	0.089	2.951***
Kernel matching	279	119	0.275	0.082	3.350***

**** Significant at 1%, ** significant at 5%, * significant at 10%. Source: survey data*

Table 3.9 shows that it is the experience of farmers in Zambia and Zimbabwe that adopting CA has a statistically significant impact on improving soil health and reducing the forest area cleared per year. The positive impact of CA on soil health is consistent with CA's soil improvement objective and Thierfelder et al. (2017), who found that CA in Southern Africa increases infiltration and reduces evaporation due to increased biological activity, beneficial to the soil's pore structure and offers surface protection through crop residues. Ikazaki et al. (2018) also found that minimum tillage and crop residue mulch reduced the annual soil loss by 54 per cent in Sudan. Crop residue mulch controls water erosion by reducing water runoff and stimulating the boring of termites that increase soil permeability (Ikazaki et al., 2018). The results further show that CA is a potential win-win solution for farmers and the environment. CA increases farmers’ food production, at the same time significantly reducing further clearance of the forest area. Our finding is consistent with Kassam and Mkomwa (2017) who state that CA technologies ensure a sustained production system that enhances environmental management and conservation. Similarly, Dumanski et al. (2006), Kassam et al. (2014) and Palm et al. (2014) also show that modern technologies such as CA not only have agronomic and social benefits but also benefit the communities through improved environmental quality and ecosystem services. Table 3.10 below highlights the differences in welfare in the two countries.

Table 3.10: Statistica differences in welfare levels between Zimbabwe and Zambia

Outcome	Zimbabwe	Zambia	mean	t-stat	P>|z|
Number of meals per day	2.729	2.892	-0.163	3.734	0.002

The outcome variables proxied for welfare were binary except the number of meals per day and the number of food-insecure months. However, the number of food-insecure months is not significantly impacted by conservation agriculture. Therefore, the only welfare outcome compared statistically is the number of meals per day. We observe in Table 3.10 that Zimbabwe farmers have access to 2.7 meals per day compared to Zambia's 2.9 meals per day. It shows that conservation agriculture has had more impact in Zambia than in Zimbabwe.

3.2 Cross-country policy lessons for CA adoption

The systematic differences between Zimbabwe and Zambia regarding the variables hypothesised to determine the probability of CA adoption are presented in Table 3.11.

Table 3.11: Descriptive statistics by country of residence

Variable	Zimbabwe (n=202)	Zambia (n=204)	t-stat (chi2)	P>|z|
Household demographic characteristics				
Age of HH head (years)	52.74	48.82	-2.716	0.007***
Maximum education level of HH head (years)	9.14	9.19	0.1437	0.886
HH head is married (%)	69.80	83.82	11.216	0.001***
Plot characteristics				
Mixed farming (%)	76.24	42.65	47.472	0.000***
Farm size (ha)	1.47	12.61	5.789	0.000***
Low soil fertility perception (%)	62.87	70.59	2.723	0.099*
Access to information, institutional services, and social capital				
Belonging to a farmer's group (%)	39.60	83.82	84.087	0.000***
Off-farm income (%)	90.10	44.61	95.356	0.000***

**** Significant at 1%, ** significant at 5%, * significant at 10%. Source: survey data*

Table 3.11 shows that farmers in Zambia and Zimbabwe significantly differ with respect to the HH head age, marital status, whether they practice mixed farming, average farm sizes, perceptions on soil fertility prior to CA adoption, whether they belong to farmer groups and whether they have access to off-farm income. We report the probit estimation results of equation (5) in Table 3.12.

Table 3.12: Probit regression of CA adoption with age and country interaction term

Variable	Coefficient	Std. Err.	Z	P>|z|
Household demographic characteristics				
Country of residence (1=Zimbabwe, 0=Zambia)	0.9792***	0.3082	3.18	0.001
Age + country	0.0205***	0.0073	2.81	0.005
Maximum education level of HH head (Years)	0.0315	0.0271	1.16	0.244
HH head is married (1=Yes, 0=No)	-0.2718	0.2333	-1.16	0.244
Plot characteristics				
Being mixed farmer (1=Yes, 0=No)	0.0383	0.2083	0.18	0.854
Inputs obtained outside HH (1=Yes, 0=No)	0.9400***	0.2843	3.31	0.001
Farm size (ha)	-0.0009	0.0111	-0.08	0.936
Soil fertility perception (1=Low, 0=High)	1.8049***	0.1919	9.41	0.000
Access to information, institutional services, and social capital				
Access to extension (1=Yes, 0=No)	0.7445***	0.2131	3.49	0.000
Belonging to a farmer's group (1=Yes, 0=No)	0.2565	0.2324	1.10	0.270
Off-farm income (1=Yes, 0=No)	-0.0822	0.2320	-0.35	0.723
Access to credit (1=Yes, 0=No)	0.8121	0.5823	1.39	0.163
Constant	-2.9770***	0.6297	-4.73	0.000
Observations	406			
LR chi2	261.67			
Prob>chi2	0.0000***			
Pseudo R2	0.5187			
Log-likelihood	-121.4236			

**** Significant at 1%, ** significant at 5%, * significant at 10%. Source: survey data*

Given the statistical significance of the county of residence dummy, we conclude that farmers in Zimbabwe are more likely to adopt CA relative to those in Zambia, and our data show a higher average age of farmers in Zimbabwe (Table 3.11). Therefore, we conclude that Zambia policymakers could potentially increase CA adoption rates by promoting the technologies among older farmers like in Zimbabwe.

We followed this approach and tested for the significance of the country dummy when interacted with farm size (farmsize + country), HH head education level (educ + country) and HH head marital status (married + country). We further tested for its interaction with whether the HH practices mixed farming (mixedfarm + country), sources inputs from outside the HH (inputs + country), has access to extension services (extension + country), belongs to a farmer group (group + country), has access to off-farm income (offarm + country), and has access to credit facilities (credit + country). We finally tested its interaction with the HHs perception on soil fertility prior to CA adoption (soil + country). We report on the results of individual probit models in the appendices (Appendix D to Appendix M), while Table 3.13 below summarises the key insights from this analysis.

Table 3.13: Key insights from individual probit models with interaction terms

Variable	Variables	Coefficient	Std. Err.	Z	P>|z|
Education	Country dummy	0.9682***	0.3109	3.11	0.002
	Educ + country	0.0315	0.0271	1.16	0.244
Married	Country dummy	1.2715***	0.3814	3.33	0.001
	Married + country	-0.2718	0.2333	-1.16	0.244
Mixed farming	Country dummy	0.9614***	0.4325	2.22	0.026
	Mixedfarm + country	0.0383	0.2083	0.18	0.854
Inputs	Country dummy	0.0597	0.2918	0.20	0.838
	Inputs + country	0.9400***	0.2843	3.31	0.001
Farm size	Country dummy	1.0006***	0.3043	3.29	0.001
	Farmsize + country	-0.0009	0.0111	-0.08	0.936
Soil	Country dummy	-0.8052**	0.3402	-2.37	0.018
	Soil + country	0.7445***	0.2131	3.49	0.000
Extension	Country dummy	0.2552	0.4113	0.62	0.535
	Extension + country	0.7445***	0.2131	3.49	0.000
Group	Country dummy	0.7432**	0.3356	2.21	0.027
	Group + country	0.2565	0.2324	1.10	0.270
Off-farm income	Country dummy	1.0820***	0.4263	2.51	0.011
	Offarm + country	-0.0822	0.2320	-0.35	0.723
Credit	Country dummy	0.1876	0.6370	0.29	0.768
	Credit + country	0.8121	0.5823	1.39	0.163

**** Significant at 1%, ** significant at 5%, * significant at 10%. Source: survey data*

We observe from Table 3.13 that the interaction terms involving sourcing for inputs from outside the HH, perceptions on whether soil fertility was low prior to CA adoption, and access to extension services had statistically significant impacts on the probability of CA adoption. However, the country dummy associated with perceptions on whether soil fertility was low prior to CA adoption is the only one that is statistically significant, emphasising the importance of such perceptions on CA adoption decisions. Although the country dummy terms of Table 3.13 suggest that Zambia policymakers could potentially increase CA adoption rates by promoting technologies among farmers who are married, practise mixed farming, have larger farm sizes, belong to farmer groups, and have access to off-farm income, these conclusions are not robust since the individual interaction terms are not statistically significant**.**

CHAPTER 4: CONCLUSIONS AND POLICY RECOMMENDATIONS

This study carried out a comparative assessment of whether conservation agriculture causally improves smallholder farmer welfare in Zambia and Zimbabwe. Using household-level data and applying the propensity score matching techniques, the results showed that CA increased total agricultural yield, total maize production, resilience to drought and adaptation to climate change. Other increments were observed in terms of the number of meals per day, food security, accumulation of productive assets, the capacity to address agricultural calendar bottlenecks, total production costs, addressing gender disparities, improving soil health and reducing the amount of forest area cleared per year in the two countries. However, CA had no impact on the number of food-insecure months and social cohesion and only a weak impact on household income. The weakly causal impact of CA on household income could perhaps reflect the commensurate increase in production costs such that the net household income decreases, while the non-significant impact of CA on the number of food-insecure months could reflect the role of post-harvest losses. Additionally, we observe that Zimbabwe farmers have access to 2.7 meals per day compared to Zambia's 2.9 meals per day. Thus, it shows that conservation agriculture has had more impact in Zambia than in Zimbabwe. We also found that farmers in Zimbabwe are more likely to adopt CA relative to Zambia. Therefore, adoption rates in Zambia could be relatively increased if policy focusses on promoting the technology among older farmers, especially those who perceive soil fertility as low.

These findings confirm the role of technology adoption and cross-country experiences with CA technologies in enhancing farmer welfare. Therefore, governments, NGOs and other development partners should increase investments in agricultural extension services to make smallholder farmers more aware of CA's potential benefits on farmer welfare outcomes. Moreover, increased investments in agricultural extension would build capacity among farmers, improve markets for inputs such as jab planters and Chaka hoes (CA specialised weeding hoes) and introduce and train farmers to use herbicides to reduce labour demands. Finally, these results indicate that it will be interesting for future research to compare the impact of CA between a country with a low CA adoption rate and a country with a high CA adoption rate.

REFERENCES

Abdulai, A. N. Impact of conservation agriculture technology on household welfare in Zambia. *Agricultural Economics,* Vol. 47(6), (2016) pp. 729-741.

Andersson, J. A. & Giller, K. E. 2012. On heretics and God's blanket salesmen: contested claims for Conservation Agriculture and the politics of its promotion in African smallholder farming. *In:* Sumberg, J. & Thompson, J. (eds.) *In Contested agronomy: Agricultural research in a changing world.* 22-46. Abingdon, UK: Earthscan, (Routledge).

Arslan, A., McCarthy, N., Lipper, L., Asfaw, S. & Cattaneo, A. Adoption and intensity of adoption of conservation farming practices in Zambia. *Agriculture, Ecosystems & Environment,* Vol. 187(13), (Rome, Italy: Food and Agriculture Organization of the United Nations,2014). pp. 72-86.

Arslan, A., McCarthy, N., Lipper, L., Asfaw, S., Cattaneo, A. & Kokwe, M. Climate smart agriculture? Assessing the adaptation implications in Zambia. *Journal of Agricultural Economics,* Vol. 66(3), (2015) pp. 753-780.

Bassett, T. J. Breaking up the bottlenecks in food-crop and cotton cultivation in northern Côte d'Ivoire. *Africa: Journal of the International African Intsitute,* Vol. 58(2), (1988) pp. 147-174.

Baudron, F., Mwanza, H., Triomphe, B. & Bwalya, M. Conservation agriculture in Zambia: a case study of Southern Province. *Nairobi. African Conservation Tillage Network, Centre de Coopération Internationale de Recherche Agronomique pour le Développement, Food and Agriculture Organization of the United Nation.,* Vol. (Kenya, Nairobi: African Conservation Tillage Network (ACT),2007).

Baudron, F., Tittonell, P., Corbeels, M., Letourmy, P. & Giller, K. E. Comparative performance of conservation agriculture and current smallholder farming practices in semi-arid Zimbabwe. *Field crops research,* Vol. 132,(2011) pp. 117-128.

Beal, S. & Kupzyk, K. An introduction to propensity scores: what, when, and how. *The Journal of Early Adolescence,* Vol. 34,(2014) pp. 66-92.

Blundell, R. & Costa Dias, M. Evaluation methods for non-experimental data. *Fiscal studies,* Vol. 21(4), (2000) pp. 427-468.

Brookhart, M. A., Schneeweiss, S., Rothman, K. J., Glynn, R. J., Avorn, J. & Stürmer, T. Variable selection for propensity score models. *American journal of epidemiology,* Vol. 163(12), (2006) pp. 1149-1156.

Caliendo, M. & Kopeinig, S. Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys,* Vol. 22(1), (2008) pp. 31-72.

Corbeels, M., de Graaff, J., Ndah, T. H., Penot, E., Baudron, F., Naudin, K., Andrieu, N., Chirat, G., Schuler, J., Nyagumbo, I., Rusinamhodzi, L., Traore, K., Mzoba, H. D. & Adolwa, I. S. Understanding the impact and adoption of conservation agriculture in Africa: A multi-scale analysis. *Agriculture, Ecosystems & Environment,* Vol. 187,(2014) pp. 155-170.

Derpsch, R., Friedrich, T., Kassam, A. & Li, H. Current status of adoption of no-till farming in the world and some of its main benefits. *International Journal of Agricultural and Biological Engineering,* Vol. 3(1), (2010) pp. 1-25.

Dumanski, J., Peiretti, R., Benites, J., McGarry, D. & Pieri, C. The paradigm of conservation agriculture. *Proc. World Assoc. Soil Water Conserv. P,* Vol. 1,(2006) pp. 58-64.

Feder, G., Just, R. E. & Zilberman, D. Adoption of agricultural innovations in developing countries: A survey. *Economic development and cultural change,* Vol. 33(2), (1985) pp. 255-298.

Food and Agriculture Organization. 2021. *Conservation Agriculture* [Online]. Available: http://www.fao.org/conservation-agriculture/en/ [Accessed 01/01/2021].

Giller, K. E., Witter, E., Corbeels, M. & Tittonell, P. A. Conservation agriculture and smallholder farming in Africa: The heretics' view. *Field Crops Research,* Vol. 114(1), (2009) pp. 23-34.

Grabowski, P. P., Haggblade, S., Kabwe, S. & Tembo, G. Minimum tillage adoption among commercial smallholder cotton farmers in Zambia, 2002 to 2011. *Agricultural Systems,* Vol. 131,(2014) pp. 34-44.

Haggblade, S. & Tembo, G. *Conservation farming in Zambia,* (Washington DC, USA: International Food Policy Research Institute (IFPRI),2003).

Heckman, J., Ichimura, H., Smith, J. & Todd, P. Characterizing selection bias using experimental data. Vol. (1998) pp. 1017-1098.

Hobbs, P. R. Conservation agriculture: what is it and why is it important for future sustainable food production? *Journal of Agricultural Science-Cambridge,* Vol. 145(2), (2007) pp. 127.

Hodges, R. J., Buzby, J. C. & Bennett, B. Postharvest losses and waste in developed and less developed countries: opportunities to improve resource use. *The Journal of Agricultural Science,* Vol. 149(S1), (2011) pp. 37-45.

Ikazaki, K., Nagumo, F., Simporé, S. & Barro, A. Are all three components of conservation agriculture necessary for soil conservation in the Sudan Savanna? *Soil Science and Plant Nutrition,* Vol. 64(2), (2018) pp. 230-237.

Jaleta, M., Kassie, M. & Shiferaw, B. Tradeoffs in crop residue utilization in mixed crop–livestock systems and implications for conservation agriculture. *Agricultural Systems,* Vol. 121,(2013) pp. 96-105.

Jumbe, C. B. L. & Nyambose, W. H. Does conservation agriculture enhance household food security? evidence from smallholder farmers in Nkhotakota in Malawi. *Sustainable Agriculture Research,* Vol. 5(1), (2016) pp. 118-128.

Kassam, A., Derpsch, R. & Friedrich, T. Global achievements in soil and water conservation: The case of Conservation Agriculture. *International Soil and Water Conservation Research,* Vol. 2(1), (2014) pp. 5-13.

Kassam, A., Friedrich, T., Shaxson, F. & Pretty, J. The spread of Conservation Agriculture: justification, sustainability and uptake. *International Journal of Agricultural Sustainability,* Vol. 7(4), (2009) pp. 292-320.

Kassam, A. & Mkomwa, S. International Conservation Agriculture advisory panel for Africa (ICAAP-Africa). *Online: www. act-africa. org,* Vol.,2017).

Kassie, M., Teklewold, H., Jaleta, M., Marenya, P. & Erenstein, O. Understanding the adoption of a portfolio of sustainable intensification practices in eastern and southern Africa. *Land Use Policy,* Vol. 42,(2015) pp. 400-411.

Khonje, M., Manda, J., Alene, A. D. & Kassie, M. Analysis of adoption and impacts of improved maize varieties in eastern Zambia. *World Development,* Vol. 66,(2015) pp. 695-706.

Kimiywe, J. Food and nutrition security: challenges of post-harvest handling in Kenya. *Proceedings of the Nutrition Society,* Vol. 74(4), (2015) pp. 487-495.

Kuntashula, E., Chabala, L. M. & Mulenga, B. P. Impact of minimum tillage and crop rotation as climate change adaptation strategies on farmer welfare in smallholder farming systems of Zambia. *Journal of Sustainable Development,* Vol. 7(4), (2014) pp. 95-110.

Kuntashula, E. & Mungatana, E. Estimating the causal effect of improved fallows on environmental services provision under farmers' field conditions in Chongwe, Zambia. *Environment and Development Economics,* Vol. 20(1), (2015) pp. 80-100.

Mango, N., Makate, C., Tamene, L., Mponela, P. & Ndengu, G. Impact of the adoption of conservation practices on cereal consumption in a maize-based farming system in the Chinyanja Triangle, Southern Africa. *Sustainable Futures*, Vol. 2,(2020) pp. 100014.

Marenya, P. P. & Barrett, C. B. Household-level determinants of adoption of improved natural resources management practices among smallholder farmers in western Kenya. *Food Policy*, Vol. 32(4), (2007) pp. 515-536.

Marongwe, L. S., Kwazira, K., Jenrich, M., Thierfelder, C., Kassam, A. & Friedrich, T. An African success: the case of conservation agriculture in Zimbabwe. *International journal of agricultural sustainability*, Vol. 9(1), (2011) pp. 153-161.

Mazvimavi, K. Socio-economic analysis of conservation agriculture in southern Africa. Vol. (FAO Regional Emergency Office for Southern Africa (REOSA), Rome, Italy,2010).

Mazvimavi, K., Ndlovu, P. V., Nyathi, P. & Minde, I. J.Conservation agriculture practices and adoption by smallholder farmers in Zimbabwe. Joint 3rd African Association of Agricultural Economists (AAAE) and 48th Agricultural Economists Association of South Africa (AEASA), 19-23 September 2010 Cape Town, South Africa.(International Crop Research Institute for the Semi Arid Tropics (ICRISAT), Zimbabwe, 1-19.2010)

Mazvimavi, K. & Twomlow, S. Socioeconomic and institutional factors influencing adoption of conservation farming by vulnerable households in Zimbabwe. *Agricultural Systems*, Vol. 101(1), (2009) pp. 20-29.

Mazvimavi, K., Twomlow, S., Belder, P. & Hove, L. An assessment of the sustainable uptake of conservation farming in Zimbabwe: Global theme on agroecosystems, Report No. 39. Vol. (International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Zimbabwe,2008).

Milder, J. C., Majanen, T. & Scherr, S. Performance and potential of conservation agriculture for climate change adaptation and mitigation in Sub-Saharan Africa. Vol. (Final Report, EcoAgriculture Partners, Virginia, United States,2011).

Mupangwa, W., Mutenje, M., Thierfelder, C. & Nyagumbo, I. Are conservation agriculture (CA) systems productive and profitable options for smallholder farmers in different agro-ecoregions of Zimbabwe? *Renewable Agriculture and Food Systems*, Vol. 32(1), (2017) pp. 87-103.

Mupangwa, W., Twomlow, S. & Walker, S. Reduced tillage, mulching and rotational effects on maize (Zea mays L.), cowpea (Vigna unguiculata (Walp) L.) and sorghum (Sorghum bicolor L.(Moench)) yields under semi-arid conditions. *Field Crops Research*, Vol. 132,(2012) pp. 139-148.

Ndlovu, P. V., Mazvimavi, K., An, H. & Murendo, C. Productivity and efficiency analysis of maize under conservation agriculture in Zimbabwe. *Agricultural Systems*, Vol. 124,(2014) pp. 21-31.

Ng'ombe, J., Kalinda, T., Tembo, G. & Kuntashula, E. Econometric analysis of the factors that affect adoption of conservation farming practices by smallholder farmers in Zambia. *Journal of Sustainable Development*, Vol. 7(4), (2014) pp. 124-138.

Ng'ombe, J. N., Kalinda, T. H. & Tembo, G. Does adoption of conservation farming practices result in increased crop revenue? Evidence from Zambia. *Agrekon*, Vol. 56(2), (2017) pp. 205-221.

Ngoma, H., Mulenga, B. P. & Jayne, T. S. What explains minimal usage of minimum tillage practices in Zambia? Evidence from district-representative data. Vol. (82), (Indaba Agricultural Policy Research Institute (IAPRI), Lusaka, Zambia,2014).

Ngwira, A. R., Thierfelder, C. & Lambert, D. M. Conservation agriculture systems for Malawian smallholder farmers: long-term effects on crop productivity, profitability and soil quality. *Renewable Agriculture and Food Systems,* Vol. 28(4), (2013) pp. 350-363.

Nkala, P., Mango, N. & Zikhali, P. Conservation agriculture and livelihoods of smallholder farmers in central Mozambique. *Journal of Sustainable Agriculture,* Vol. 35(7), (2011) pp. 757-779.

Nyamangara, J., Nyengerai, K., Masvaya, E., Tirivavi, R., Mashingaidze, N., Mupangwa, W., Dimes, J., Hove, L. & Twomlow, S. Effect of conservation agriculture on maize yield in the semi-arid areas of Zimbabwe. *Experimental agriculture,* Vol. 50(2), (2013) pp. 159 - 177.

Nyanga, P. H., Johnsen, F. H. & Kalinda, T. H. Gendered impacts of conservation agriculture and paradox of herbicide use among smallholder farmers. *International Journal of Technology and Development Studies,* Vol. 3(1), (2012) pp. 1-24.

Ogada, M. J., Rao, E. J. O., Radeny, M., Recha, J. W. & Solomon, D. Climate-smart agriculture, household income and asset accumulation among smallholder farmers in the Nyando basin of Kenya. *World Development Perspectives,* Vol. 18(100203), (2020) pp. 1-11.

Palm, C., Blanco-Canqui, H., DeClerck, F., Gatere, L. & Grace, P. Conservation agriculture and ecosystem services: An overview. *Agriculture, Ecosystems & Environment,* Vol. 187,(2014) pp. 87-105.

Pedzisa, T., Rugube, L., Winter-Nelson, A., Baylis, K. & Mazvimavi, K. The Intensity of adoption of Conservation agriculture by smallholder farmers in Zimbabwe. *Agrekon,* Vol. 54(3), (2015) pp. 1-22.

Rockström, J., Kaumbutho, P., Mwalley, J., Nzabi, A. W., Temesgen, M., Mawenya, L., Barron, J., Mutua, J. & Damgaard-Larsen, S. Conservation farming strategies in East and Southern Africa: Yields and rain water productivity from on-farm action research. *Soil and Tillage Research,* Vol. 103(1), (2009) pp. 23-32.

Rosenbaum, P. R. & Rubin, D. B. The central role of the propensity score in observational studies for causal effects. *Biometrika,* Vol. 70(1), (1983) pp. 41-55.

Rubin, D. B. Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of educational Psychology,* Vol. 66(5), (1974) pp. 688-701.

Shula, R. K., Hamisi, M., Mwanza, H., Mpanda, M., Muriuki, J. & Mkomwa, S. (2012), Policies and institutional arrangements relevant to conservation agriculture with trees in Zambia. World Agroforestry Centre Report.

Simasiku, P., Chapoto, A., Richardson, R. B., Sichilongo, M., Tembo, G., Weber, M. T. & Zulu, A. Natural resource management, food security, and rural development in Zambia: moving from research evidence to action. Proceedings of the public forum. Vol. (44), (Working Paper No. 44, Indaba Agricultural Policy Research Institute (IAPRI), Lusaka, Zambia,2010). pp. 47.

Siziba, S., Nyikahadzoi, K., Makate, C. & Mango, N. Impact of conservation agriculture on maize yield and food security: Evidence from smallholder farmers in Zimbabwe. *African Journal of Agricultural and Resource Economics,* Vol. 14(2), (2019) pp. 89-105.

Smith, J. A. & Todd, P. E. Does matching overcome LaLonde's critique of nonexperimental estimators? *Journal of econometrics,* Vol. 125(1-2), (2005) pp. 305-353.

Thierfelder, C., Cheesman, S. & Rusinamhodzi, L. A comparative analysis of conservation agriculture systems: benefits and challenges of rotations and intercropping in Zimbabwe. *Field crops research,* Vol. 137,(2012) pp. 237-250.

Thierfelder, C., Chivenge, P., Mupangwa, W., Rosenstock, T. S., Lamanna, C. & Eyre, J. X. How climate-smart is conservation agriculture (CA)? - its potential to deliver on adaptation, mitigation and productivity on smallholder farms in southern Africa. *Food*

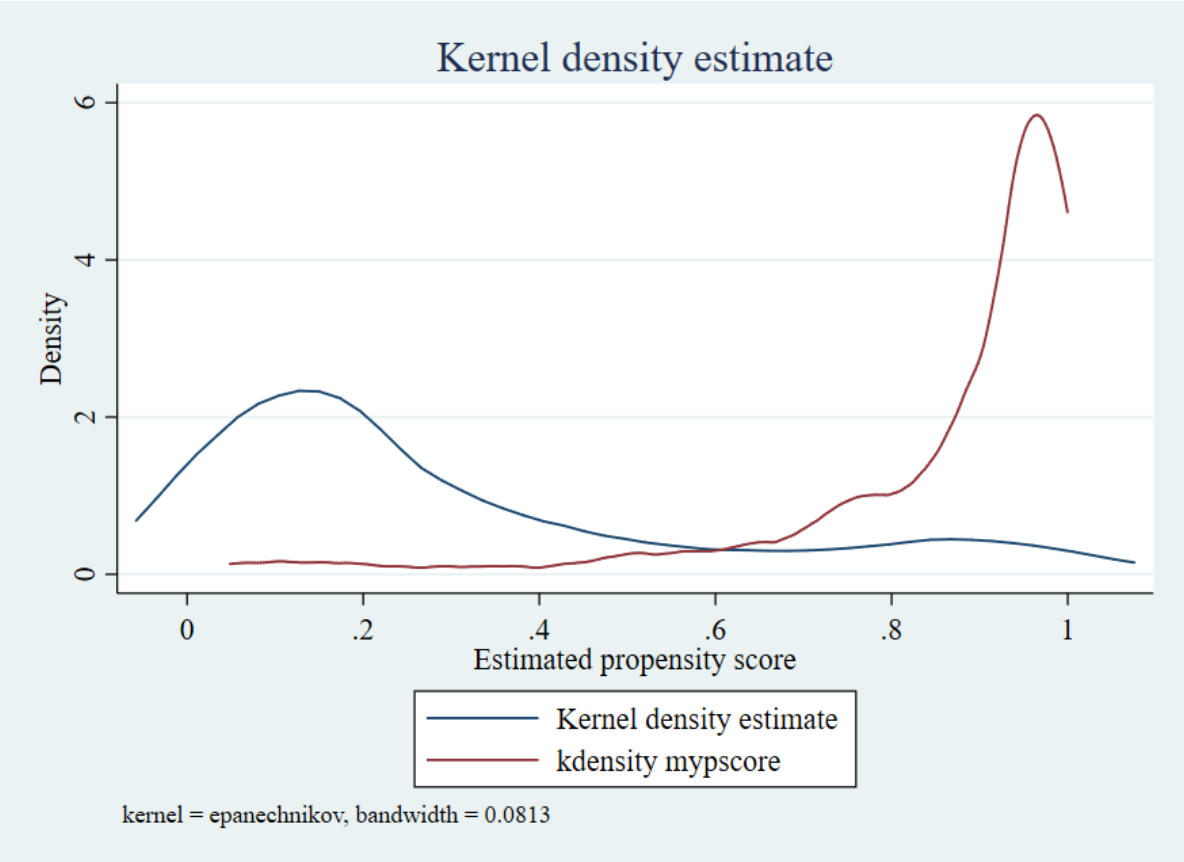
Security : The Science, Sociology and Economics of Food Production and Access to Food, Vol. 9(3), (2017) pp. 537-560.

Twomlow, S., Urolov, J., Jenrich, M. & Oldrieve, B. Lessons from the field–Zimbabwe's Conservation Agriculture Task Force. *Journal of SAT Agricultural Research,* Vol. 6(1), (2008) pp. 1-11.

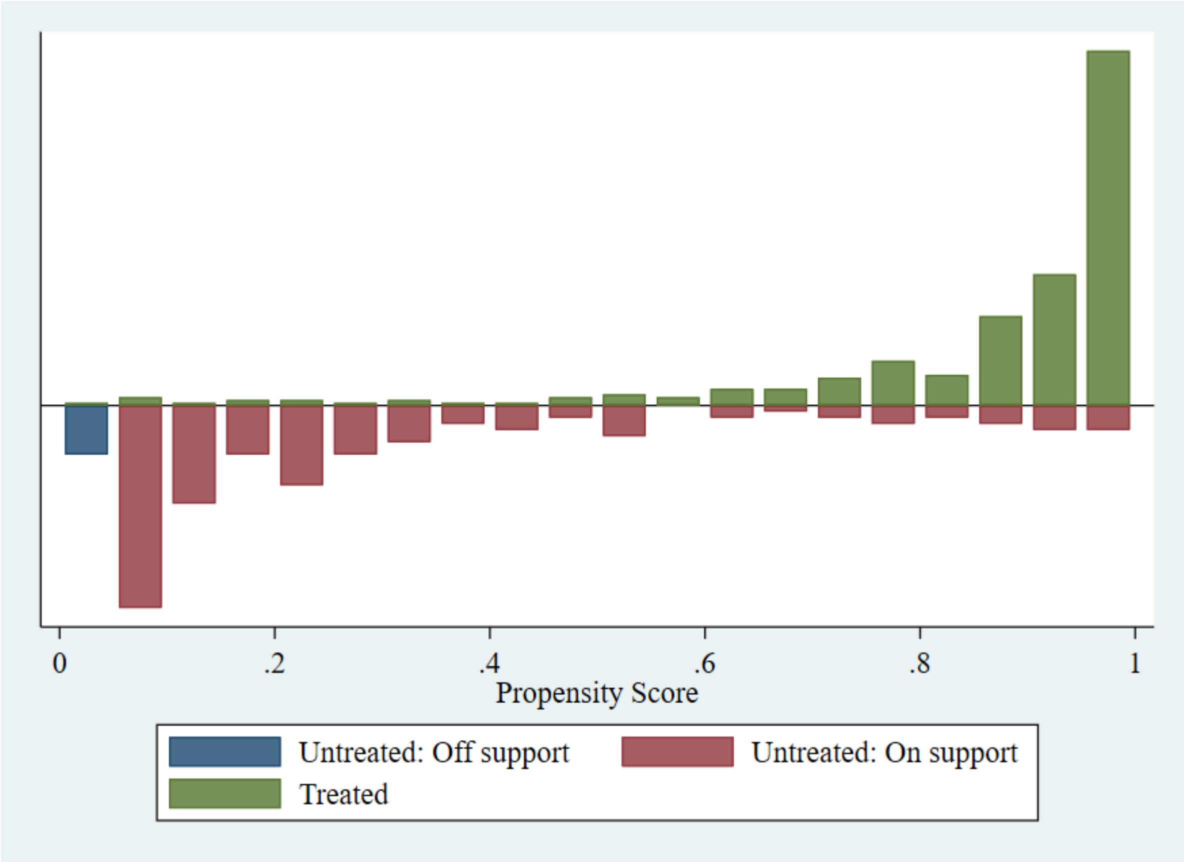
Umar, B. B., Aune, J. B., Johnsen, F. H. & Lungu, O. I. Options for improving smallholder conservation agriculture in Zambia. *Journal of Agricultural Science,* Vol. 3(3), (2011) pp. 50-62.

Wooldridge, J. M. *Introduction to econometrics*, (Andover, Hampshire: Cengage Learning,2013).

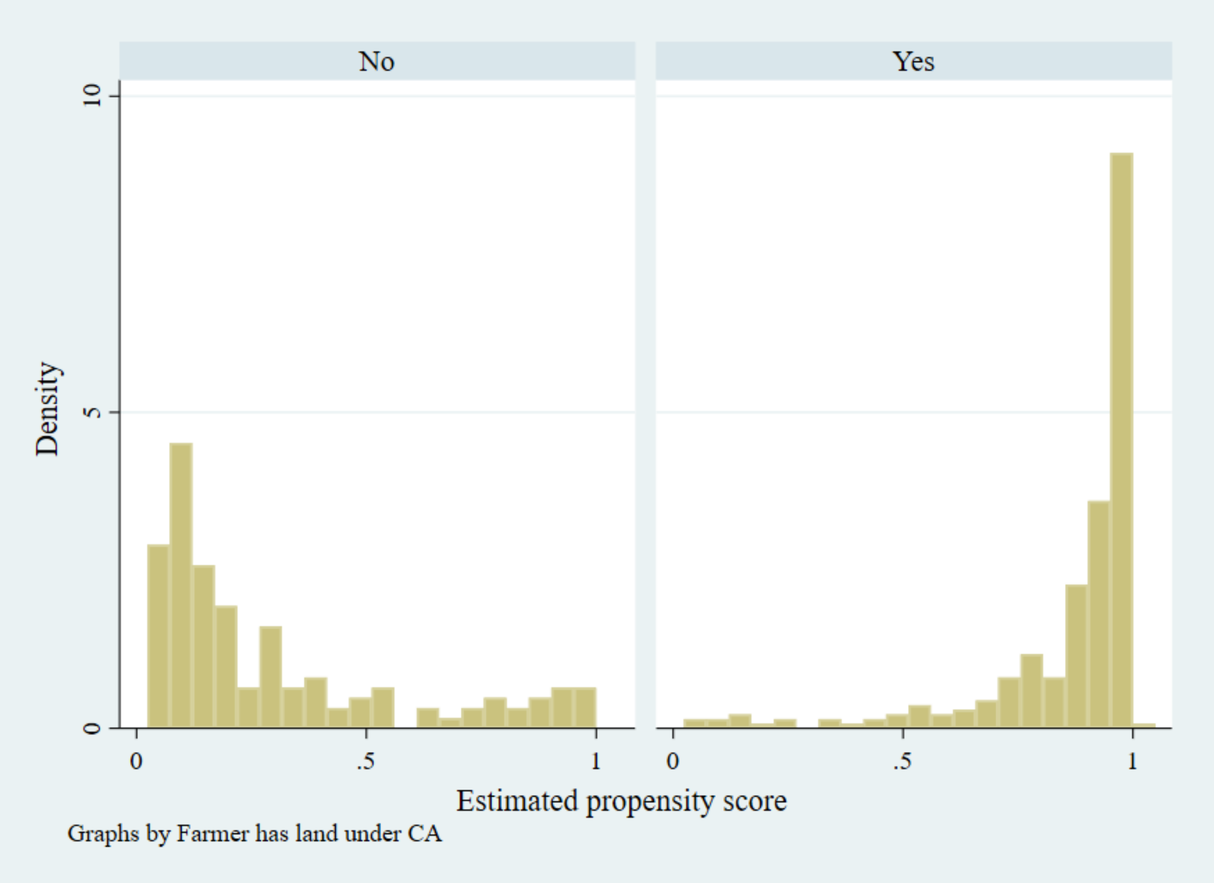
APPENDICES



Appendix A: Kernel density distribution showing the overlap between adopters and non-adopters of CA



Appendix B: The distribution of estimated propensity scores between treated and control groups



Appendix C: The distribution of estimated propensity scores between adopters and non-adopters of CA

Appendix D: Probit regression of CA adoption with education and country interaction term

Adoption of CA (treat)	Coef.	Std. Err.	Z	P>|z|
Country dummy (1=Zimbabwe, 0=Zambia)	0.9682	0.3109	3.11	0.002
Educ + country	0.0315	0.0271	1.16	0.244
Age of HH head (years)	0.0205	0.0073	2.81	0.005
HH head is married (I=Yes, 0=No)	-0.2718	0.2333	-1.16	0.244
Inputs obtained outside HH (1=Yes, 0=No)	0.9400	0.2843	3.31	0.001
Being mixed farmer (1=Yes, 0=No)	0.0383	0.2083	0.18	0.854
Farm size (ha)	-0.0009	0.0111	-0.08	0.936
Soil fertility before CA (1=Low, 0=High)	1.8049	0.1919	9.41	0.000
Access to extension (1=Yes, 0=No)	0.7445	0.2131	3.49	0.000
Belonging to farmer group (1=Yes, 0=No)	0.2565	0.2324	1.10	0.270
Off-farm income access (1=Yes, 0=No)	-0.0822	0.2320	-0.35	0.723
Access to credit (1=Yes, 0=No)	0.8121	0.5823	1.39	0.163
Constant	-2.9770	0.6297	-4.73	0.000
Observations	406			
LR chi2	261.67			
Prob>chi2	0.0000			
Pseudo R2	0.5187			
Log-likelihood	-121.4236			

*** *Significant at 1%, ** significant at 5%, * significant at 10%. Source: survey data*

Appendix E: Probit regression of CA adoption with marital status and country interaction term

Adoption of CA (treat)	Coef.	Std. Err.	Z	P>|z|
Country dummy (1=Zimbabwe, 0=Zambia)	1.2715	0.3814	3.33	0.001
Married + country	-0.2718	0.2333	-1.16	0.244
Age of HH head (years)	0.0205	0.0073	2.81	0.005
Maximum education level of HH head (years)	0.0315	0.0271	1.16	0.244
Inputs obtained outside HH (1=Yes, 0=No)	0.9400	0.2843	3.31	0.001
Being mixed farmer (1=Yes, 0=No)	0.0383	0.2083	0.18	0.854
Farm size (ha)	-0.0009	0.0111	-0.08	0.936
Soil fertility before CA (1=Low, 0=High)	1.8049	0.1919	9.41	0.000
Access to extension (1=Yes, 0=No)	0.7445	0.2131	3.49	0.000
Belonging to farmer group (1=Yes, 0=No)	0.2565	0.2324	1.10	0.270
Off-farm income access (1=Yes, 0=No)	-0.0822	0.2320	-0.35	0.723
Access to credit (1=Yes, 0=No)	0.8121	0.5823	1.39	0.163
Constant	-2.9770	0.6297	-4.73	0.000
Observations	406			
LR chi2	261.67			
Prob>chi2	0.0000			
Pseudo R2	0.5187			
Log-likelihood	-121.4236			

**** Significant at 1%, ** significant at 5%, * significant at 10%. Source: survey data*

Appendix F: Probit regression of CA adoption with mixed farming and country interaction term

Adoption of CA (treat)	Coef.	Std. Err.	Z	P>|z|
Country dummy (1=Zimbabwe, 0=Zambia)	0.9614	0.4325	2.22	0.026
Mixedfarm + country	0.0383	0.2083	0.18	0.854
Age of HH head (years)	0.0205	0.0073	2.81	0.005
Maximum education level of HH head (Years)	0.0315	0.0271	1.16	0.244
HH head is married (I=Yes, 0=No)	-0.2718	0.2333	-1.16	0.244
Inputs obtained outside HH (1=Yes, 0=No)	0.9400	0.2843	3.31	0.001
Farm size (ha)	-0.0009	0.0111	-0.08	0.936
Soil fertility before CA (1=Low, 0=High)	1.8049	0.1919	9.41	0.000
Access to extension (1=Yes, 0=No)	0.7445	0.2131	3.49	0.000
Belonging to farmer group (1=Yes, 0=No)	0.2565	0.2324	1.10	0.270
Off-farm income access (1=Yes, 0=No)	-0.0822	0.2320	-0.35	0.723
Access to credit (1=Yes, 0=No)	0.8121	0.5823	1.39	0.163
Constant	-2.9770	0.6297	-4.73	0.000
Observations	406			
LR chi2	261.67			
Prob>chi2	0.0000			
Pseudo R2	0.5187			
Log-likelihood	-121.4236			

*** *Significant at 1%, ** significant at 5%, * significant at 10%. Source: survey data*

Appendix G: Probit regression of CA adoption with inputs sourced from outside and country interaction term

Adoption of CA (treat)	Coef.	Std. Err.	Z	P>|z|
Country dummy (1=Zimbabwe, 0=Zambia)	0.0597	0.2918	0.20	0.838
Inputs + country	0.9400	0.2843	3.31	0.001
Age of HH head (years)	0.0205	0.0073	2.81	0.005
Maximum education level of HH head (Years)	0.0315	0.0271	1.16	0.244
HH head is married (I=Yes, 0=No)	-0.2718	0.2333	-1.16	0.244
Being mixed farmer (1=Yes, 0=No)	0.0383	0.2083	0.18	0.854
Farm size (ha)	-0.0009	0.0111	-0.08	0.936
Soil fertility before CA (1=Low, 0=High)	1.8049	0.1919	9.41	0.000
Access to extension (1=Yes, 0=No)	0.7445	0.2131	3.49	0.000
Belonging to farmer group (1=Yes, 0=No)	0.2565	0.2324	1.10	0.270
Off-farm income access (1=Yes, 0=No)	-0.0822	0.2320	-0.35	0.723
Access to credit (1=Yes, 0=No)	0.8121	0.5823	1.39	0.163
Constant	-2.9770	0.6297	-4.73	0.000
Observations	406			
LR chi2	261.67			
Prob>chi2	0.0000			
Pseudo R2	0.5187			
Log-likelihood	-121.4236			

**** Significant at 1%, ** significant at 5%, * significant at 10%. Source: survey data*

Appendix H: Probit regression of CA adoption with farm size and country interaction term

Adoption of CA (treat)	Coef.	Std. Err.	Z	P>|z|
Country dummy (1=Zimbabwe, 0=Zambia)	1.0006	0.3043	3.29	0.001
Farmsize + country	-0.0009	0.0111	-0.08	0.936
Age of HH head (years)	0.0205	0.0073	2.81	0.005
Maximum education level of HH head (Years)	0.0315	0.0271	1.16	0.244
HH head is married (I=Yes, 0=No)	-0.2718	0.2333	-1.16	0.244
Being mixed farmer (1=Yes, 0=No)	0.0383	0.2083	0.18	0.854
Inputs obtained outside HH (1=Yes, 0=No)	0.9400	0.2843	3.31	0.001
Soil fertility before CA (1=Low, 0=High)	1.8049	0.1919	9.41	0.000
Access to extension (1=Yes, 0=No)	0.7445	0.2131	3.49	0.000
Belonging to farmer group (1=Yes, 0=No)	0.2565	0.2324	1.10	0.270
Off-farm income access (1=Yes, 0=No)	-0.0822	0.2320	-0.35	0.723
Access to credit (1=Yes, 0=No)	0.8121	0.5823	1.39	0.163
Constant	-2.9770	0.6297	-4.73	0.000
Observations	406			
LR chi2	261.67			
Prob>chi2	0.0000			
Pseudo R2	0.5187			
Log-likelihood	-121.4236			

**** Significant at 1%, ** significant at 5%, * significant at 10%. Source: survey data*

Appendix I: Probit regression of CA with soil fertility perception before CA adoption and country interaction term

Adoption of CA (treat)	Coef.	Std. Err.	Z	P>|z|
Country dummy (1=Zimbabwe, 0=Zambia)	-0.8052	0.3402	-2.37	0.018
Soil + country	0.7445	0.2131	3.49	0.000
Age of HH head (years)	0.0205	0.0073	2.81	0.005
Maximum education level of HH head (Years)	0.0315	0.0271	1.16	0.244
HH head is married (I=Yes, 0=No)	-0.2718	0.2333	-1.16	0.244
Being mixed farmer (1=Yes, 0=No)	0.0383	0.2083	0.18	0.854
Inputs obtained outside HH (1=Yes, 0=No)	0.9400	0.2843	3.31	0.001
Farm size (ha)	-0.0009	0.0111	-0.08	0.936
Access to extension (1=Yes, 0=No)	0.7445	0.2131	3.49	0.000
Belonging to farmer group (1=Yes, 0=No)	0.2565	0.2324	1.10	0.270
Off-farm income access (1=Yes, 0=No)	-0.0822	0.2320	-0.35	0.723
Access to credit (1=Yes, 0=No)	0.8121	0.5823	1.39	0.163
Observations	406			
LR chi2	261.67			
Prob>chi2	0.0000			
Pseudo R2	0.5187			
Log-likelihood	-121.4236			

*** Significant at 1%, ** significant at 5%, * significant at 10%. Source: survey data*

Appendix J: Probit regression of CA adoption with extension by CA promoters and country interaction term

Adoption of CA (treat)	Coef.	Std. Err.	Z	P>|z|
Country dummy (1=Zimbabwe, 0=Zambia)	0.2552	0.4113	0.62	0.535
Extension + country	0.7445	0.2131	3.49	0.000
Age of HH head (years)	0.0205	0.0073	2.81	0.005
Maximum education level of HH head (Years)	0.0315	0.0271	1.16	0.244
HH head is married (I=Yes, 0=No)	-0.2718	0.2333	-1.16	0.244
Being mixed farmer (1=Yes, 0=No)	0.0383	0.2083	0.18	0.854
Inputs obtained outside HH (1=Yes, 0=No)	0.9400	0.2843	3.31	0.001
Farm size (ha)	-0.0009	0.0111	-0.08	0.936
Soil fertility before CA (1=Low, 0=High)	1.8044	0.1918	9.41	0.000
Belonging to farmer group (1=Yes, 0=No)	0.2565	0.2324	1.10	0.270
Off-farm income access (1=Yes, 0=No)	-0.0822	0.2320	-0.35	0.723
Access to credit (1=Yes, 0=No)	0.8121	0.5823	1.39	0.163
Observations	406			
LR chi2	261.67			
Prob>chi2	0.0000			
Pseudo R2	0.5187			
Log-likelihood	-121.4236			

**** Significant at 1%, ** significant at 5%, * significant at 10%. Source: survey data*

Appendix K: Probit regression of CA adoption with farming group and country interaction term

Adoption of CA (treat)	Coef.	Std. Err.	Z	P>|z|
Country dummy (1=Zimbabwe, 0=Zambia)	0.7432	0.3356	2.21	0.027
Group + country	0.2565	0.2324	1.10	0.270
Age of HH head (years)	0.0205	0.0073	2.81	0.005
Maximum education level of HH head (Years)	0.0315	0.0271	1.16	0.244
HH head is married (I=Yes, 0=No)	-0.2718	0.2333	-1.16	0.244
Being mixed farmer (1=Yes, 0=No)	0.0383	0.2083	0.18	0.854
Inputs obtained outside HH (1=Yes, 0=No)	0.9400	0.2843	3.31	0.001
Farm size (ha)	-0.0009	0.0111	-0.08	0.936
Soil fertility before CA (1=Low, 0=High)	1.8044	0.1918	9.41	0.000
Access to extension (1=Yes, 0=No)	0.7445	0.2131	3.49	0.000
Off-farm income access (1=Yes, 0=No)	-0.0822	0.2320	-0.35	0.723
Access to credit (1=Yes, 0=No)	0.8121	0.5823	1.39	0.163
Observations	406			
LR chi2	261.67			
Prob>chi2	0.0000			
Pseudo R2	0.5187			
Log-likelihood	-121.4236			

**** Significant at 1%, ** significant at 5%, * significant at 10%. Source: survey data*

Appendix L: Probit regression of CA adoption with off-farm income and country interaction term

Adoption of CA (treat)	Coef.	Std. Err.	Z	P>|z|
Country dummy (1=Zimbabwe, 0=Zambia)	1.0820	0.4263	2.51	0.011
Income + country	-0.0822	0.2320	-0.35	0.723
Age of HH head (years)	0.0205	0.0073	2.81	0.005
Maximum education level of HH head (Years)	0.0315	0.0271	1.16	0.244
HH head is married (I=Yes, 0=No)	-0.2718	0.2333	-1.16	0.244
Being mixed farmer (1=Yes, 0=No)	0.0383	0.2083	0.18	0.854
Inputs obtained outside HH (1=Yes, 0=No)	0.9400	0.2843	3.31	0.001
Farm size (ha)	-0.0009	0.0111	-0.08	0.936
Soil fertility before CA (1=Low, 0=High)	1.8044	0.1918	9.41	0.000
Access to extension (1=Yes, 0=No)	0.7445	0.2131	3.49	0.000
Belonging to farmer group (1=Yes, 0=No)	0.2565	0.2324	1.10	0.270
Access to credit (1=Yes, 0=No)	0.8121	0.5823	1.39	0.163
Observations	406			
LR chi2	261.67			
Prob>chi2	0.0000			
Pseudo R2	0.5187			
Log-likelihood	-121.4236			

*** *Significant at 1%, ** significant at 5%, * significant at 10%. Source: survey data*

Appendix M: Probit regression of CA adoption with credit access and country interaction term

Adoption of CA (treat)	Coef.	Std. Err.	Z	P>|z|
Country dummy (1=Zimbabwe, 0=Zambia)	0.1876	0.6370	0.29	0.768
Credit + country	0.8121	0.5823	1.39	0.163
Age of HH head (years)	0.0205	0.0073	2.81	0.005
Maximum education level of HH head (Years)	0.0315	0.0271	1.16	0.244
HH head is married (I=Yes, 0=No)	-0.2718	0.2333	-1.16	0.244
Being mixed farmer (1=Yes, 0=No)	0.0383	0.2083	0.18	0.854
Inputs obtained outside HH (1=Yes, 0=No)	0.9400	0.2843	3.31	0.001
Farm size (ha)	-0.0009	0.0111	-0.08	0.936
Soil fertility before CA (1=Low, 0=High)	1.8044	0.1918	9.41	0.000
Access to extension (1=Yes, 0=No)	0.7445	0.2131	3.49	0.000
Belonging to farmer group (1=Yes, 0=No)	0.2565	0.2324	1.10	0.270
Off-farm income access (1=Yes, 0=No)	-0.0822	0.2320	-0.35	0.723
Observations	406			
LR chi2	261.67			
Prob>chi2	0.0000			
Pseudo R2	0.5187			
Log-likelihood	-121.4236			

**** Significant at 1%, ** significant at 5%, * significant at 10%. Source: survey data*