Impact of conservation agriculture on maize yield and food security: Evidence from smallholder farmers in Zimbabwe

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Abstract

Conservation agriculture is promoted as a green technology that enhances the productivity and food security of farmers. However, there is limited evidence from practising farmers regarding these expected outcomes. This study evaluates the impact of conservation agriculture on the productivity of maize and food security outcomes among smallholder farmers in Zimbabwe. The propensity score-matching approach was used to estimate the impact. The data is based on a 2013 survey of 488 households. Conservation agriculture, largely defined by the use of planting basins, had a positive and significant ($p < 0.05$) impact on maize grain yield (ATT = 473 kgha^{-1}), with the magnitude more pronounced among female-headed households (ATT = 515.53 kgha^{-1}). The increased grain production extended the households' grain self-provision period by 1.14 months for the pooled sample, and by a slightly longer period of 2.89 months for the female-headed sample. The study concludes that conservation agriculture increases maize productivity and grain supply to households, particularly for female-headed households.

Key words: conservation agriculture; food security; impact; propensity score matching; Zimbabwe

1. Introduction

Conservation agriculture (CA) in Zimbabwe has received a lot of research and promotional support from international agricultural research centres, as well as from the Food and Agriculture Organization (FAO), since the mid-1980s (FAO 2007). Conservation agriculture is largely promoted as one of the few win-win technologies that are affordable for farmers in the sense that it potentially improves farmers' yields (in the long term), while at the same time conserving the environment (Giller *et al*. 2009; Marongwe *et al*. 2011). The few on-farm and on-station trials that have been conducted indicate that conservation agriculture improves maize yield by margins ranging from 5% to 90% (Mazvimavi & Twomlow 2009). Soil water retention can be improved, cushioning crops from moisture stress during prolonged dry spells, which are becoming more frequent in Southern Africa (SA). This advantage is very relevant in the face of the region being predicted to become drier

(Intergovernmental Panel on Climate Change [IPCC] 2014). However, Giller *et al*. (2009) have raised some concern over the feasibility of conservation agriculture on smallholder farms, given the constraining biophysical and institutional realities under which farmers operate. For example, residue retention is difficult due to competition by livestock, particularly in drier regions. A key requirement for a technology to be adopted sustainably is that it should yield tangible benefits for farmers (Cary & Wilkinson 1997; Pannell 1999). Various studies using household-level data (Arslan *et al*. 2015; Kassie *et al*. 2015; Michler *et al*. 2018; Steward *et al*. 2018) and experimental data (Mupangwa *et al*. 2012; Ngwira *et al*. 2013; Thierfelder *et al*. 2015; Kiboi *et al*. 2017; Mupangwa *et al*. 2017) show positive yield effects from conservation agriculture. These studies do not, however, go on to measure the impact of conservation agriculture on household food security – the tangibility of the expected benefit.

The overall objective of this study was to answer the basic question – whether adoption of conservation agriculture is resulting in tangible gains in smallholder farmers' food security levels. The study adopts the propensity score-matching method to evaluate the impact following Heckman *et al*. (1997). The findings of this study make valuable contributions to the current debate on the merits of conservation agriculture and its likely adoption by farmers in the long run.

2. Methodology

To address the question of the tangibility of the benefits of conservation agriculture, the study employed the impact assessment approach pioneered by Rosenbaum and Rubin (1983). Specifically, we applied propensity score matching to identify the impact of conservation agriculture.

Conservation agriculture comprises a suite of practices. It has three important principles: 1) minimal soil disturbance, 2) permanent soil cover and 3) crop rotation[1] (FAO 2001). Minimum soil disturbance and permanent soil cover help in improving the organic matter content of the soil, reducing water run-off due to increased infiltration as well as ensuring increased soil biological activity. The use of mulch is particularly important for infiltration and the reduction of evaporation. The biophysical transformations offset by practising conservation agriculture are expected to result in a sustained increase in crop yields (Erenstein 1999). If conservation agriculture fails to that give rise to tangible benefits that would be at the forefront of farmers' interest, such as increased food or income, the prospects for its widespread adoption are low (Cary & Wilkinson 1997; Pannell 1999).

2.1 Measuring impact: The counterfactuals framework

Rosenbaum and Rubin (1983) developed a potential outcomes framework that helps to conceptualise and measure impact. Under this framework, each household has two potential outcomes ex ante: an outcome (food security level) when treated (adopting conservation agriculture) that we denote Y_1, and an outcome when not treated (not adopting conservation agriculture) that we denote Y_0. Let the binary variable D stand for treatment status, with D = 1 for treated and $D = 0$ for not treated. Then the observed outcome of Y for any household can be expressed as a function of two potential outcomes: $Y = DY_1 + (1\text{-}D)\ Y_0$. For any household, the causal effect of the adoption of conservation agriculture on its observed outcome Y is simply the difference between its two potential outcomes: $Y_1 - Y_0$. It is impossible for the two potential outcomes to be realised at the same time because they are mutually exclusive for any household. It is therefore impossible to measure the individual effect of the adoption of conservation agriculture on any given household. However, at the population level, $E\ (Y_1 – Y_0)$ (where E is the expectation operator) gives what is referred to in the literature as the average treatment effect (ATE). The ATE measures the average treatment effect on a randomly selected individual in

[1] For a more detailed technical discussion on how each of the conservation agriculture principles works towards the realisation of the desired goals, see Dumanski *et al*. (2006).

the population. It is also possible to estimate the mean effect of the adoption of conservation agriculture on the sub-population of conservation agriculture adopters: $E\ (Y_1 - Y_0|D = 1)$, which is called the average treatment effect on the treated, denoted ATT. Furthermore, the average treatment effect on the untreated, denoted as ATE0, is measured as $E\ (Y_1 - Y_0|D = 0)$.

With randomised experimental design data, direct estimation of the ATE will consistently estimate the impact or causal effect. However, with observational data, there are problems of overt and hidden biases and endogeneity of the treatment variable, which result in inconsistent ATE estimation. Several methods can be found in the statistics and econometric literature for removing or minimising the effects of these biases (see Imbens & Wooldridge, 2009). These methods generally fall into two categories: those that remove overt biases only, and those that also correct for unobservable biases. The appropriateness of the method depends on the plausibility of the assumption made about the source of the biases (Imbens & Wooldridge 2009). We adopt the propensity score-matching method to minimise biases.

2.2 Propensity score matching

In a nutshell, the impact-identification strategy of matching approaches is based on locating, among the untreated, a group of individuals that is as close as possible to the treated individuals in terms of some set of observable pre-treatment characteristics. The missing counterfactual outcomes are replaced by the outcomes of the closely matching individuals. The treatment effect is estimated as the difference in outcomes of the two comparable groups.

According to Todd (2006), the starting assumption of matching methods is that there exists a set of observed pre-treatment characteristics Z, such that the outcomes are independent of treatment conditional on Z. That is, the outcomes (Y_0, Y_1) are independent of the treatment status D, conditional on *Z*.

$$(Y_1, Y_0) \perp D|Z \qquad \text{(conditional independence assumption)} \qquad (1)$$

It is also assumed that for all Z there exists a positive probability of either being treated (D = 1) or untreated (D = 0), i.e.

$$0 < \Pr\ (D = 1|Z) < 1 \quad \text{(overlap or common support assumption)} \qquad (2)$$

Under these assumptions, the mean impact on the treated can be written as

$$\begin{aligned} \Delta &= E\ (Y_1 - Y_0)\ |D = 1) \\ &= E\ (Y_1|D = 1) - E_{z|D=1}\{E_Y\ (Y|D = 1, Z)\} \\ &= E\ (Y_1|D = 1) - E_{z|D=1}\{E_y\ (Y|D = 1, Z)\}, \end{aligned} \qquad (3)$$

where the second term can be estimated from the mean outcomes of the matched (on Z) comparison group. The propensity score-matching technique we adopt in this study has been widely applied in the agricultural economics literature to correct for self-selection bias in impact studies (Faltermeier & Abdulai 2009; Akinola & Sofoluwe 2012; Mapila *et al*. 2012; Makate *et al*. 2017; Mango *et al*. 2017). Hence, it is a reliable approach for the study objective. We used the Stata psmatch2 command developed by Leuven and Sianesi (2003) to estimate the impact.

Impact estimators

There are a number of algorithms for matching based on the propensity score. The matching estimators have tended to improve over time. They include the more traditional matching methods –

typically the one-on-one nearest-neighbour matching. Then there are simple, smoothed matching methods, such as *k* nearest neighbours, caliper, and radius matching. More recently developed are weighted smoothed matching methods, which include kernel-based matching and local linear regression-based matching (Todd 2006). The nearest neighbour matching (NNM) method matches each farmer from the treated group with the farmer from the untreated group having the closest propensity score. The matching can be done with or without the replacement of observations. Caliper matching is a variation of NNM that attempts to avoid "bad" matches (where distance between matches is too large) by imposing a tolerance on the maximum distance allowed. A disadvantage of caliper matching is that the distances are unknown a priori. The kernel-based matching method constructs a match for each treated individual using a weighted average over multiple persons in the comparison group (Todd 2006). We adopted the kernel-matching estimator because it is more efficient and also because valid standard errors of the estimates can be generated through bootstrapping (Abadie *et al*. 2004).

2.3 Measuring outcome variables

2.3.1 Maize yields

The maize yields ($kgha^{-1}$) were measured as the total grain harvested (kg) from a plot divided by the plot size (ha). The harvest figures were based on farmer recall, although this may not have been very accurate. We nonetheless do not expect any systematic differences in the recall errors among adopters and non-adopters.

2.3.2 Food security

Food security is attained when all people at all times have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life (FAO 1996; Swindale & Bilinsky 2005). On the basis of this definition, the key pillars of food security are: availability, accessibility, utilisation and stability. We measure food security at the household level using two indicators: food consumption score (FCS), and length of grain self-provision period.

2.3.3 Food consumption score

The food consumption score, as outlined by the World Food Programme and the Food and Agriculture Organization ([WFP-FAO] 2008), is calculated using the frequency of consumption of different food groups consumed by a household during the seven days before the survey. It captures both the quality and quantity of people's diet at the household level. The formula used to compute the food consumption score is as follows:

$$FCS = a \times f(staple) + a \times f(pulse) + a \times f(vegetables) + a \times f(fruit) + a \times f(animal) + a \times f(sugar) + a \times f(dairy) + a \times f(oil),$$

where FCS = food consumption score, f = frequency of food consumption (number of days for which each food group was consumed during the preceding seven days, and a = weight/nutritional value of each food group.

The main limitation of the food consumption score is that it is only a snapshot of one week of food consumption and so fails to capture seasonal changes. It, however, remains a widely used proxy for household food security. Various other studies have used the food consumption score as a measure of household food security (Mango *et al*. 2015; Makate *et al*. 2016; Mango *et al*. 2017).

2.3.4 Period of grain self-provision

We measured the period of grain self-provisioning as the number of months the farmer household lasted with its own maize harvest. Maize is the predominant and staple crop grown by smallholder farmers in Zimbabwe. Its production is targeted mostly at meeting own cereal grain requirement. Anecdotal evidence shows that many farmers run out of maize grain before the next harvest and have to resort to other sources, mostly buying from the market, to cope with the grain shortage. For the many cash- and resource-constrained farmers, this means food (grain) insecurity.

2.4. The treatment variable – conservation agriculture

In Zimbabwe, the typical components of conservation agriculture that are being extended to smallholder farmers are: the reduced tillage, which is largely achieved by using planting basins or minimum tillage equipment; leaving of plant residues on the surface to act as mulch; crop rotation; timely weeding (commonly manual); and the use of organic and chemical fertilisers. However, observations on the ground show that farmers faced with some constraints often fail to incorporate all the components (see Mazvimavi *et al*. 2010). In this study, a farmer was deemed to be a CA adopter if at least 50% of his/her cultivated maize area was under minimum tillage – either through basins or the use of minimum-till equipment. Although the use of minimum tillage was a central consideration, it can be seen from Table 3 (later in this paper) that these CA farmers also used complementary practices, such as crop rotation, residue retention and herbicides, to varying degrees. We expect that such farmers are relatively closer to making the complete switch to conservation agriculture.

2.5 Sampling and data collection

The study collected primary data in 2013 from three districts in Zimbabwe where conservation agriculture has been promoted since 2005 and continues to be promoted, namely Shamva, Wedza and Masvingo (see map in Figure 1). In all the selected districts, the promotion of conservation agriculture is done by government extension officers in collaboration with NGOs. Individual households were randomly selected in each district. A minimum of 50 households practising conservation agriculture at any level, and 80 farmers not using conservation agriculture at all, were selected in each district. There were slight deviations from these target sample sizes in the field (see Table 1). Table 1 gives a breakdown of the survey households by district. The data was collected from a total of 488 households for the whole study.

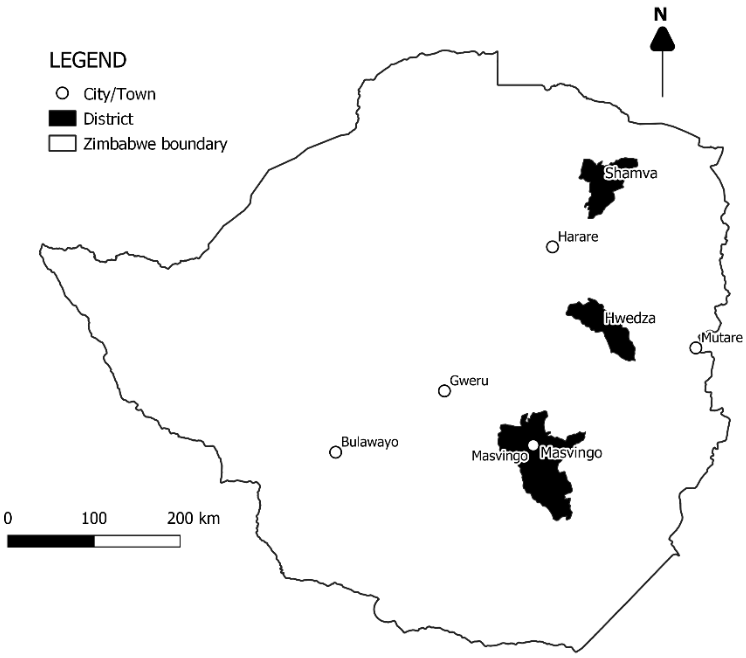

Figure 1: A map of Zimbabwe showing the location of the study areas

Table 1: Sample distribution by district

District	CA users N (%)	Non-users N (%)	Sub-sample N (%)
Shamva	66 (37)	113 (63)	179 (100)
Wedza	61 (41)	88 (59)	149 (100)
Masvingo	75 (47)	85 (53)	160 (100)
Total	202 (41)	286 (59)	488 (100)

3. Results and discussion

3.1 Characteristics of farmer households

Table 2 summarises selected characteristics of the farmer households in the survey. We present the results for the entire sample (all farmers), and for the sub-sample of female-headed households (women farmers). For all the farmers, only about a fifth (20.9%) qualified as CA adopters, and this proportion was slightly larger among women farmers (25%). There was a significant difference ($p < 0.1$) in the gender composition of CA adopters and non-adopters: the adopters of conservation agriculture represented more female-headed households than the non-adopters (43% vs. 33%). The adopters and non-adopters of conservation agriculture also differed in terms of the marital status of the household head for the pooled data. The CA adopters had fewer married heads, with more single people (6.86% vs. 2.07%) and widows (32.35% vs. 26.17%) than the non-adopters. Among the sub-sample of women, the marital status of the household heads was more homogenous, but dominated strikingly by widows (around 70%). There were no differences between adopters and non-adopters for the other socioeconomic variables. It is notable, however, that the sub-group of women tended to have a lower education level, were older, and had more farm experience when compared to the values for the entire sample.

It is important to point out that farmers who were practising conservation agriculture also had portions of land under conventional farming, and only rain-fed maize production was considered. Very few CA farmers practised conservation agriculture exclusively. All farmers cultivated maize; for non-CA farmers this was exclusively under conventional tillage, while the CA farmers used both farming types. Both types of farmers had more or less the same total acreage under maize, at about three-quarters of a hectare (0.71 ha for CA and 0.74 ha for non-CA). Adopters of conservation agriculture had about 90% of their maize area under conservation agriculture, and the percentage was slightly lower among women farmers (84%). The maize area put under basins by adopters was relatively small, at a mean of 0.43 ha for all farmers and 0.38 ha for women farmers. The basal fertilisation (mostly with compound D) rates on maize were not statistically different between the CA (95 $kgha^{-1}$) and non-CA farmers (110 $kgha^{-1}$), although notably much less for women farmers in both cases (80 vs. 89 $kgha^{-1}$). Farmers using conservation agriculture used significantly more labour for maize than non-CA farmers: 396 vs 309 person days ha^{-1} for all farmers and 406 vs. 294 person days ha^{-1} for women farmers. Conservation agriculture adopters achieved significantly higher maize yields than non-CA adopters for both samples – for all farmers (1 621 $kgha^{-1}$ vs. 1 298 $kgha^{-1}$) and for women farmers (1 576 $kgha^{-1}$ vs. 1 190 $kgha^{-1}$). There were statistically significant differences in the grain self-provision period and the food consumption score (Table 2).

3.2 Conservation practices used by CA adopters

As indicated earlier, a suite of practices is encouraged under conservation agriculture to complement reduced soil tillage. Table 3 shows the practices used by farmers who were classified as adopters in the study. The majority (93% to 97.7%) of farmers adopted planting basins to achieve minimum tillage, while a few (< 7%) used a draught-drawn implement (ripper or direct seeders). Notably few farmers used herbicides and cover crops. About 40% of the farmers retained crop residue for mulch. However, poor yields, roaming livestock and competing uses (such as fodder, composting and fuel) limit the quantity of crop residue coverage.

3.3 Impact of CA adoption

We estimated the impact of conservation agriculture on three outcomes: maize yield, grain self-provision period, and the food consumption score. The impact on the three outcome variables was estimated at two levels: the aggregated sample, and the sub-group of female-headed households. In all the impact models, we used the following Z or conditioning covariates: age, gender (except for women), education level, farming experience, asset endowment level (principal component analysis derived), cattle owned, and farm size (total cultivated land area). Table 4 shows the definition of the covariates used.

Table 2: Characteristics of farmers

Attribute	All farmers			Women farmers		
	CA adopter N = 102	CA non-adopter N = 386	t/chi-square test P-value	CA adopter N = 80	CA non-adopter N = 93	t/chi-square test P-value
Socioeconomic characteristics						
Proportion of sample (%)	20.9	79.1		25.4	74.6	
Gender of household head (prop. male)	0.57	0.67	0.0683	100	100	
Age of household head (mean years)	52.7 (14.7)	53.5 (14.7)	0.6406	55.7 (12.6)	57.2 (12.6)	0.5182
Marital status (%)						
single	6.86	2.07		11.36	3.88	
married	56.86	67.88		13.64	13.18	
widowed	32.35	26.17		70.45	73.64	
divorced	3.92	3.89	0.034	4.55	9.3	0.246
Education (mean years)	8.05 (3.17)	7.93 (3.30)	0.7387	7.05 (3.05)	6.25 (3.22)	0.1521
Household size (mean)	4.97 (2.06)	5.14 (2.23)	0.4885	4.52 (2.11)	4.74 (2.37)	0.5834
Dependency ratio (mean)	2.52 (1.55)	2.65 (1.72)	0.4951	2.32 (1.84)	2.33 (1.40)	0.9779
Farming experience (mean years)	20.41 (14.32)	20.57 (14.49)	0.9217	25.20 (15.15)	25.12 (14.08)	0.9719
Outcome variables						
Total maize area (ha)	0.71 (0.55)	0.74 (0.43)	0.5467	0.63 (0.46)	0.67 (0.31)	0.4970
Proportion of maize area under CA	0.90 (0.49)	0	0.0000***	0.84 (0.30)	0.07 (0.13)	0.0000***
Maize area under CA (ha)	0.43 (0.28)	0	0.0000***	0.38 (0.16)	0.06 (0.11)	0.0000***
Maize basal fertilisation rate (kg of compound per ha)	95.79 (117.38)	110.13 (103.03)	0.1538	80.4 (99.79)	89.36 (85.86)	0.5267
Labour use (person days per ha)	396.44 (323.24)	309.15 (220.13)	0.0001***	406.49 (343.31)	294.08 (215.83)	0.0027***
Maize yield (mean kgha^{-1})	1 620.96 (1 163.99)	1 297.55 (827.68)	0.0015**	1 575.76 (1 036.07)	1 190.58 (816.51)	0.0129**
Grain self-provision (mean months)	10.71 (4.17)	10.96 (5.00)	0.6328	11.02 (3.74)	10.27 (5.02)	0.3643
Food consumption score (mean)	65.02 (18.73)	63.87 (19.90)	0.5975	66.59 (17.75)	63.51 (18.89)	0.3446

Notes: 1. Asterisks, *, ** and ***, denote statistically significant differences at the $p < 0.1$, $p < 0.05\%$ and $p < 0.001\%$ levels respectively with t-test or chi-square test. 2. Standard deviations are in brackets

Table 3: Conservation agriculture practices used by adopters of conservation agriculture

Practice	All farmers	Women farmers
	% practising	% practising
Draught-drawn equipment (ripper, direct seeder)	6.9	4.6
Basins	93.14	97.7
Herbicides	3.9	0
Rotation	39.2	27.3
Cover crops	4.9	4.6
Residue retention	46.08	36.4

Table 4: Definition of covariates used for matching

Variables	Description
GENDER	Dummy for gender of household head; 1 = male, 0 = female
AGE	Age of household head in years
GENDER x AGE	Interactions of gender and age of household
AGE x AGE	Age of household squared
EDUC_YRS	Education of household head in years of formal schooling
AGE x EDUC	Interaction of age and education
HH_SIZE	Number of members in the household
FARM_YRS	Farming experience in years
ASSET	Principal component analysis-derived household asset ownership score
CATTLE	Herd size of cattle owned
CULTV_AREA	Total land cultivated by farmer in 2012 season in ha
CLAY_SOIL_D	Dummy indicating whether soil type of farmer's plot is clay; 1 = clay; 0 = otherwise
SHAMVA_D	Dummy indicating whether farmer is located in Shamva; 1 = Shamva, 0 = otherwise
WEDZA_D	Dummy indicating whether farmer is located in Wedza; 1 = Wedza, 0 = otherwise

3.4 The models selected

Before presenting the ATT estimates, we show the results of the first-stage probit models and check for the quality of matching. The probit regression model is used to compute the propensity score used for the matching method. The objective of this selection model is not to explain the adoption of conservation agriculture as exactly as possible, but to form the basis for eliminating the observed and non-observed differences between the treated and non-treated in the matching procedure (Gelübcke 2012). Table 5 shows the probit regression estimation for all the farmers and for the sub-sample of women. The probit models had a reasonable fit, with a significant LR test ($P < 0.05$).

Table 5: First-stage probit regressions for the kernel method

CA_adopt	Pooled data		Sub-sample of women	
	Coefficient	t	Coefficient	t
GENDER	-0.597	-0.95	-	-
GENDER x AGE	0.007	0.64	-	-
AGE	-0.002	-0.04	-0.133	-1.55
AGE x AGE	0.000	0.00	0.001	1.00
EDUC_YRS	0.044	0.39	-0.278	-1.33
AGE x EDUC	0.000	0.00	0.007	1.75*
HH_SIZE	-0.004	-0.12	-0.029	-0.48
FARM_YRS	0.007	1.00	0.013	1.08
ASSET	0.027	0.57	0.043	0.51
CATTLE	-0.701	-3.92***	-0.914	-2.91***
CULTV_AREA	-0.531	-3.14***	-1.769	-3.91***
CLAY_SOIL_D	-0.262	-0.60	0.897	1.50
SHAMVA_D	0.344	1.87**	0.072	0.20
WEDZA_D	0.476	2.56**	0.355	1.09
_CONS	-0.415	-0.24	5.184	1.78
N	484		170	
Log likelihood	-218.822		-72.948	
Prob > chi^2	0.000		0.000	
Pseudo R^2	0.122		0.2496	

Asterisks, *, **, and ***, denote statistically significant differences at the p < 0.1, p < 0.05% and p < 0.001% levels respectively

3.5 Matching quality

We checked for the plausibility of the confoundedness and overlap assumption necessary for the impact identification with the propensity score-matching method. Figure 2 shows the propensity distributions of the treated and control farmers for the models. In both cases, the distributions are similar and there is good overlap. Only a few cases for the female-headed model were off the common support. Tables 6 and 7 show the mean values of variables for the CA adopters and non-adopters before and after propensity score matching. Before matching there were significant differences between the CA adopters (treated) and non-CA adopters for the pooled data in respect of the following variables: gender, asset endowment, cattle owned, cultivated land area, and being located in Wedza district. The matching procedure produces a new sample, with 484 pairs of one CA and one non-CA farmer. In this new sample, the balance between the CA and non-CA adopters has been increased for all variables, resulting in no statistical difference for all the considered covariates. The matching for the sub-sample of women was equally good.

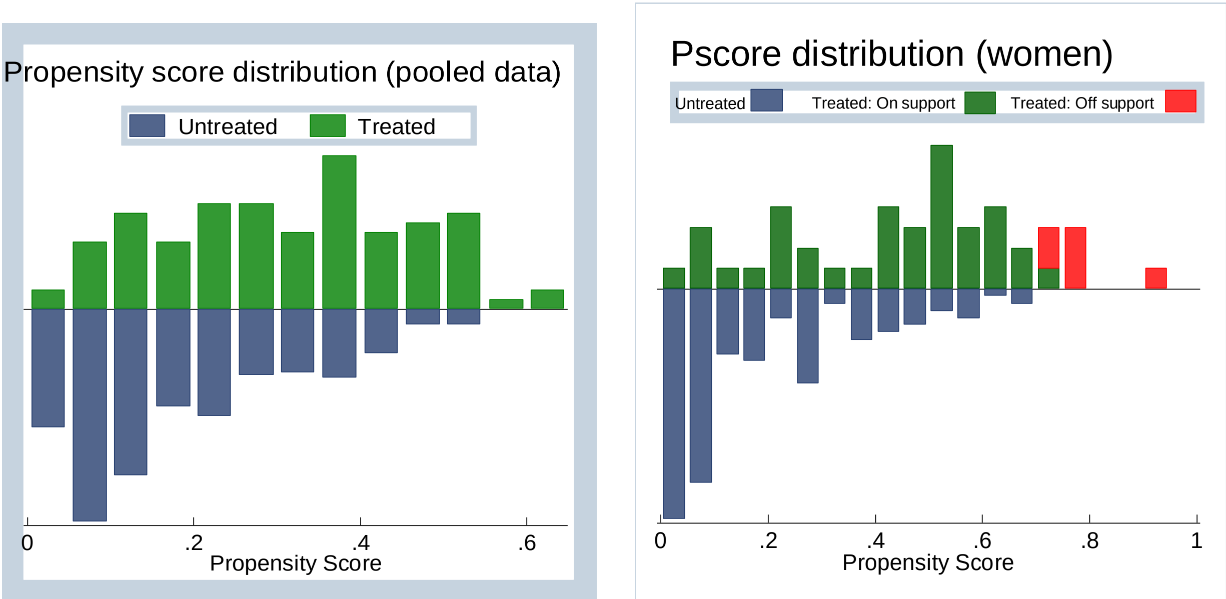

Figure 2: Propensity score distribution for the treated and untreated

Table 6: Mean values for adopters (treated) and non-adopters (control) before and after propensity score matching for pooled data

Variable	Unmatched (N = 488) / Matched (N = 484)	Mean Treated	Mean Control	t-test	P-value
AGE	U	52.74	53.50	-0.47	0.640
	M	52.74	51.82	0.45	0.651
GENDER	U	0.57	0.67	-1.95	0.052*
	M	0.57	0.58	-0.17	0.866
AGExGENDER	U	28.70	34.74	-1.97	0.049**
	M	28.70	29.28	-0.15	0.881
AGE xAGE	U	2 995.10	3 077.90	-0.46	0.647
	M	2 995.10	2 880.90	0.52	0.607
EDUC_YRS	U	8.05	7.93	0.33	0.743
	M	8.05	8.36	-0.69	0.491
AGE xEDUC	U	402.88	400.13	0.15	0.882
	M	402.88	414.80	-0.51	0.608
HH_SIZE	U	4.97	5.13	-0.67	0.504
	M	4.97	4.96	0.02	0.980
FARM_YRS	U	20.41	20.61	-0.12	0.903
	M	20.41	19.51	0.46	0.645
ASSET	U	-0.71	0.20	-3.75	0.000***
	M	-0.71	-0.63	-0.32	0.751
CATTLE	U	0.36	0.69	-6.29	0.000***
	M	0.36	0.37	-0.12	0.903
CULTV_AREA	U	0.74	1.09	-4.39	0.000***
	M	0.74	0.79	-0.77	0.439
CLAYD	U	0.02	0.04	-0.96	0.337
	M	0.02	0.02	-0.03	0.975
SHAMVA_D	U	0.38	0.36	0.42	0.672
	M	0.38	0.39	-0.05	0.958
WEDZA_D	U	0.39	0.29	2.06	0.039**
	M	0.39	0.41	-0.19	0.852

Asterisks, *, **, and ***, denote statistically significant differences at the $p < 0.1$, $p < 0.05\%$ and $p < 0.001\%$ levels respectively

Table 7: Mean values for adopters (treated) and non-adopters (control) before and after propensity score matching for the sub-sample of women

Variable	Unmatched (N = 173)	Mean		t-test	P-value
	Matched (N = 170)	Treated	Control		
AGE	U	55.73	57.19	-0.66	0.510
	M	55.32	56.23	-0.33	0.739
AGE xAGE	U	3 261.4	3 430.1	-0.66	0.508
	M	3 190.4	3 309.6	-0.38	0.703
EDUC_YRS	U	7.05	6.22	1.47	0.143
	M	7	6.86	0.20	0.838
AGE xEDUC	U	385.73	337.74	1.64	0.103
	M	380.16	380.86	-0.20	0.848
HH_SIZE	U	4.52	4.74	-0.53	0.598
	M	4.55	4.45	0.19	0.848
FARM_YRS	U	25.21	25.38	-0.07	0.944
	M	24.42	23.41	0.33	0.743
ASSET	U	-1.089	-0.318	-2.34	0.020**
	M	-1.128	-1.168	0.10	0.921
CATTLE	U	0.34	0.69	-4.34	0.000***
	M	0.39	0.40	-0.06	0.955
CULTV_AREA	U	0.62	0.96	-4.70	0.000***
	M	0.67	0.67	0.04	0.965
CLAYD	U	0.045	0.048	-0.07	0.946
	M	0.053	0.048	-0.07	0.96
SHAMVA_D	U	0.25	0.29	-0.48	0.631
	M	0.26	0.34	-0.73	0.47
WEDZA_D	U	0.48	0.34	1.57	0.118
	M	0.5	0.41	0.80	0.42

Asterisks, *, **, and ***, denote statistically significant differences at the $p < 0.1$, $p < 0.05\%$ and $p < 0.001\%$ levels respectively

3.6 Estimated ATT

Matching can be done using different algorithms. For the sake of comparison, we present the results for our matching algorithm of choice, namely kernel matching, together with those of the nearest neighbour matching method (NNM). Generally, the two methods should not produce markedly different estimates if applied appropriately (see Imbens and Wooldridge, 2009). Table 8 shows the estimated impacts of conservation agriculture on the three outcomes across the two samples. For the kernel method, the standard errors of the impact coefficient (ATT) were derived from bootstrapping 50 times with replacement. The estimated ATTs in all cases are comparable between NNM and kernel-based matching. We shall limit our discussion of the results to kernel-based matching because of the more reliable standard errors.

3.6.1 Results for all farmers

For the pooled data, conservation agriculture had a positive and significant impact on maize yield and grain self-provision. The impact on the food consumption score was not significant. The magnitude of the impact on maize yield was quite marked, at 473 kgha^{-1} . This means that, on average, a farmer who practised conservation agriculture achieved maize yields per ha that were 473 kg higher than a comparable farmer who did not practise conservation agriculture. The increased productivity is expected to improve the availability of maize grain at the household level. Households, most of whom fail to produce enough to last to the next harvest, may extend the time period they last with their own harvest – thereby delaying having to buy. The ATT of the grain self-provision period of 1.14 months was positive and significant, meaning that CA farmers lasted longer with their own grain harvest.

Conservation agriculture did not have a significant impact on the food consumption score (FCS). This means that conservation agriculture did not change the dietary range consumed by farmers.

3.6.2 Women farmers

As in the pooled data, conservation agriculture positively and significantly increased maize yield and months of self-provisioning among women farmers. Notably for both outcomes, the magnitude of the ATT was much higher when compared to the pooled data. Women CA farmers achieved yield gains of 515.53 kgha^{-1} on average, and lasted an additional 2.89 months with own harvest compared to the non-CA women. Conservation agriculture thus made a huge difference among female-headed farmers. This could be accounted for by the fact that female-headed households are usually poor, and have limited resources. They tend to plant late because they lack the draught power to prepare their land with a conventional plough. With planting basins, early planting is possible and this, in addition to the higher efficiency of the conservation agriculture system, could explain the big difference in maize yields between the two systems when managed by female-headed households.

Table 8: Estimation of impact of adopting CA on selected outcomes

		NNM			Kernel		
	N	ATT	SE	t	ATT	SE	Z
Pooled data							
Maize yield	484	430.00***	141.13	3.05	473.00***	127.91	3.70
Grain self provision	484	1.44**	0.64	2.25	1.14**	0.48	2.36
Food consumption score	484	4.87	2.68	1.81	3.20	2.48	1.29
Women							
Maize yield	170	556.17	220.50	1.18	515.53***	176.88	2.91
Grain self provision	170	3.25***	1.13	2.87	2.89***	1.11	2.59
Food consumption score	170	5.41	4.57	1.18	2.52	5.56	0.45

Notes: ATT is the average treatment effect on the treated; SE = standard error; NNM = nearest neighbour matching method; SE for NNM does not take into account that the propensity score is estimated. The SEs for the kernel method were generated by bootstrapping 50 times with replacement. Asterisks, *, **; and ***, denote statistical significance at the $p < 0.1$, $p < 0.05\%$, and $p < 0.001\%$ levels respectively.

Overall, the results point to a significant impact of conservation agriculture on maize yields and grain self-provisioning in Zimbabwe. The empirical work supports the findings, particularly the positive impact of conservation agriculture on maize yields. Both household-level studies (Arslan *et al*. 2015; Kassie *et al*. 2015; Michler *et al*. 2018; Steward *et al*. 2018) and on-farm or on-station trials (Mupangwa *et al*. 2012; Ngwira *et al*. 2013; Thierfelder *et al*. 2015; Kiboi *et al*. 2017; Mupangwa *et al*. 2017) support our findings. The insignificant impact of conservation agriculture on the food consumption score also corroborates the findings of Mango *et al*. (2017). The food consumption score embodies other food items beyond the cereal supplied by maize. This may explain why conservation agriculture did not have an impact on this broader measure of food security.

3.7 Sensitivity analysis

The propensity score-matching method uses observable covariates to eliminate bias; it remains unknown whether the estimated ATTs are affected by unobserved factors. Rosenbaum's bounds test is commonly applied to check the extent to which the ATT estimates are sensitive to possible unobservable biases. The basic idea of the Rosenbaum and Rubin (1985) bounds approach is to identify the extent to which unobserved variables would have biased the results to jeopardise their robustness (Gelübcke 2012). A gamma coefficient (γ) gives the degree to which a scenario departs from the ideal case of no further biases. The Rosenbaum bounds give significant levels for whether or not to reject the hypothesis that the ATT may result completely from hidden bias for each gamma scenario. The higher the γ can be without rejecting the aforementioned hypothesis, the less sensitive are the ATT results to hidden biases, hence robust. We used the ado-file rbounds of DiPrete and Gangl

(2004) in STATA to run the Rosenbaum bounds test. Table 9 shows the results of this robustness test. The results show that, for estimating the impact of the maize yield under pooled data, the maximum to which γ can be increased before the upper bound of the p-value exceeds 0.05 is 1.3. The gamma value is relatively small (< 2), therefore the ATT is not robust as it is sensitive to hidden biases. For the pooled data, the ATT of grain self-provision again is vulnerable to hidden biases, as γ is small (1.3). The ATT estimates for the sub-sample of women are more robust, with a γ of 1.6 for maize yield and 2.2 for grain provision. Although a positive impact was observed for the maize yield and grain self-provision, causality is more certain with the sub-sample of women and less so with the pooled data.

Table 9: Rosebaum sensitivity analysis

	Gamma (γ)	**Significance levels (Wilcoxon signed-rank test)**		**Hodges-Lehmann point estimates**		**95% confidence intervals**	
		lower	upper	lower	upper	lower	upper
maize yield (pooled)	1	0.0016	0.00156	315.59	315.59	547.33	108.74
	1.1	0.00037	0.005522	368.57	271.28	595.58	64.77
	1.2	0.00008	0.015084	406.72	223.91	655.36	20.96
	1.3	**0.00002**	**0.033778**	**444.80**	**192.00**	**701.92**	**-13.62**
	1.4	3.70E-06	0.064776	480.87	155.56	748.27	-47.53
grain self-provision (pooled)	1	0.001526	0.001526	1.36929	1.36929	2.16813	0.49453
	1.1	0.00036	0.005388	1.54448	1.15803	2.32872	0.31479
	1.2	0.000081	0.01469	1.69619	1.02148	2.47941	0.08438
	1.3	**0.00002**	**0.032871**	**1.86275**	**0.865858**	**2.61764**	**-0.06766**
	1.4	3.70E-06	0.06304	2.00663	0.693197	2.76576	-0.21794
maize yield (women)	1	0.002396	0.002396	482.125	482.125	793.331	156.774
	1.2	0.000445	0.009592	544.144	401.781	873.592	62.2473
	1.4	0.000082	0.02544	594.058	334.703	984.742	-0.45686
	1.6	**0.000015**	**0.052124**	**666.563**	**295.673**	**1049.79**	**-54.802**
	1.8	2.70E-06	0.089889	723.896	236.822	1109.77	-97.6343
grain self-provision (women)	1	0.00023	0.00023	2.92636	2.92636	4.24408	1.6144
	1.2	0.00003	0.001262	3.27378	2.60346	4.65005	1.15634
	1.4	3.90E-06	0.004239	3.52194	2.28267	4.92605	0.82784
	1.6	5.00E-07	0.01047	3.78594	2.06591	5.23837	0.42440
	1.8	6.50E-08	0.021054	3.98907	1.87767	5.53458	0.06976
	2	8.50E-09	0.036648	4.16813	1.70959	5.79011	-0.22737
	2.2	**1.10E-09**	**0.057414**	**4.31641**	**1.53928**	**5.98178**	**-0.46309**
	2.4	1.50E-10	0.0831	4.45555	1.34184	6.14995	-0.64256

4. Conclusion

The study applied a novel econometric approach to evaluate the performance of conservation agriculture in the real world of smallholder farmers. Observational data from farmers' fields was used to estimate the productivity effects of conservation agriculture and the subsequent impact on household food security. The propensity score-matching approach was used to remove observable biases in the estimation of impact. To account for the influence of hidden biases on estimated impacts, a robustness test was applied.

The study shows that conservation agriculture has a significant positive effect on maize yield and the period of grain self-provision – a gross indicator of food security. However, conservation agriculture had no impact on the food consumption score, a more comprehensive measure of food security accounting for both the quality and quantity of food intake. The impacts not very robust to hidden biases, however. When a sub-sample of female-headed households was analysed, the outcomes were more nuanced. Among female-headed households, conservation agriculture had a larger and more robust impact on both maize yield and the period of self-provisioning. Women are generally more resource constrained, and their conventional farming is characterised by the low use of key inputs such as organic and inorganic fertilisers. As shown in this study, their level of basal fertilisation of maize was much lower than that of the sample average. Because women farmers do not own livestock, they also tend to plough late in the season, thereby reducing potential yield. With conservation agriculture, farmers prepare basins off-season and so do not suffer late planting. Planting into basins also conserves moisture and concentrates the small amount of fertiliser used, thus increasing its effectiveness, as shown by Ncube *et al*. (2006). These factors may combine to explain the bigger yield impact of conservation agriculture among female farmers observed in this study. These impacts of conservation agriculture on maize yield (473 $kgha^{-1}$ and 550 $kgha^{-1}$) are quite substantial, given the low productivity levels (< 1 000 $kgha^{-1}$) among smallholder farmers in Zimbabwe. However, these gains in yield come at an increased labour usage, particularly among the female farmers. This may present an adoption barrier, given that women are already overburdened with many other household chores, such as cooking, fetching water and child rearing, among others.

We conclude that conservation agriculture makes a positive difference in productivity and food grain supply, particularly among female-headed households, which usually comprise the poor in rural communities. However, this comes at an increased labour usage. The study calls for measures to reduce labour usage, for example through affordable mechanisation for smallholder farmers. The study thus supports continuous and systematic scaling (both vertical and horizontal) of conservation agriculture practices in smallholder farming in Zimbabwe, which should be gender inclusive to ensure significant and long-lasting benefits for society arising from conservation agriculture.

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