CONSERVATION AGRICULTURE AMONG SMALLHOLDERS IN MOZAMBIQUE: A MATCHED COHORT ANALYSIS OF CAUSAL ESTIMANDS

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Abstract: Conservation agriculture (CA) has been an important part of development in many developed countries, especially as a solution to increase food production among smallholder farmers. This study focuses on the impact of CA on smallholder household wellbeing. It uses survey data representing groups of CA adopters and CA non-adopter in the Tete and Barue regions, Mozambique. The study uses several matching estimators to account for the differences in household wellbeing using similar observable characteristics among farmers' households. The propensity score matching method with variant options was used to obtain matched observations of CA adopters and non-adopters. The coarsened exact matching method was also used to account for the impact

In terms of impact, CA adopters realized higher wellbeing indices on asset index and house construction index than they would have had if they had not adopted CA. However, there is no difference between CA adopters and non-adopters in terms of the animal index. The reason attributed to this insignificance maybe because of the residue retention requiring farmers to leave crop residue on farms to retain soil moisture instead of feeding livestock with the plant residues.

This study recommends increased efforts of ongoing CA extension in the area of study.

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CHAPTER I

INTRODUCTION

1.1 Background

Seventy-five billion tons of soil degradation costs approximately US400 billion to the world annually (Eswaran et al., 1997). In terms of productivity, soil degradation occurs as a discrepancy between land quality and land use (Beinorth et al., 1991). The decline in agricultural productivity caused by land degradation threatens efforts to mitigate poverty and increase food insecurity, in developing countries. Such problems are common in countries like Mozambique, where farmers have limited access to agricultural inputs, new technologies and institutional knowledge about sustainable farming practices (Manganhele, 2010; Filimone et al., 2014). Mozambique is located in Southeast Africa, with an estimated population of 29 million inhabitants (World Bank, 2019). Agriculture in Mozambique is one of the most important economic sectors contributing to 23 percent of the country's Gross Domestic Product (GDP) and employing about 80 percent of the labor force (USAID, 2019).

The poverty rate in Sub-Saharan African (SSA) countries remains high, despite numerous efforts to increase access to jobs and markets. The promotion of agricultural technology in many African countries has been implemented to increase food productivity caused by poor agricultural practices, which eventually lead to lower soil fertility (Kassie et al., 2007; Omilola, 2009).

In other locations, the promotion of agricultural technology in some Asian economies during the world food crisis of 1970s has been successful in boosting food production and feeding the population (Lipton et Longhurst, 1989; Rosegrant et Svendsen, 1993; Saleth, 2002).

Lower soil fertility is caused by many factors. Many SSA countries still use conventional tillage practices, resulting in the loss of soils suitable for row crop production (Guto et al., 2011). In response to this issue, the Mozambican government and numerous non-governmental organizations (NGOs) have promoted conservation agriculture (CA) since 2008 in an attempt to increase soil fertility and reduce erosion (Grabowski et al., 2013). Conservation agriculture is a set of agronomic systems, which includes farming practices adapted to crop varieties and agroecosystems while optimizing yields. According to the FAO (2019), CA follows three guiding principles, including no-tillage or minimum soil disturbance, maintenance of a permanent soil cover, and rotation of crop varieties. These three practices improve soil moisture-holding capacity, retain nutrients, and increase productivity.

1.2 Problem Statement

Previous researches suggest that CA practices increase crop productivity and potentially reduce household poverty in developing countries (Khonje et al., 2014; Zeng et al., 2015; Mango et al. 2017; Abdulai et al., 2019). However, there is little information about the effects of CA technology on household wellbeing. For example, McNair et al. (2015) established correlation between CA and household wellbeing as measured by livestock and material ownership. This study extends to McNair et al.'s (2015) previous work, which only analyzed the correlation between CA and household wellbeing among smallholders in Mozambique. Thus, it did not establish causality between CA adoption and the wellbeing of smallholder farmers in Mozambique. This thesis establishes a causal link between CA indicators using propensity score matching method and coarsened exact matching.

1.3 Research Objective

The objective of this study was to determine the effects of CA adoption on smallholder household wellbeing in Mozambique.

1.4 Research Hypotheses

Smallholder farmers are simultaneously involved in consumption and production, therefore making it appropriate to use the agricultural household model (AHM) in this study (Chayanov, 1986). The household model assumes that smallholders will maximize household wellbeing subject to farm production technology. The household's optimization problem is;

$$\max_{c_i, q_i} U\left(c_{i,} q_i\,; Z_u\right)$$

subject to

$$q\left(q_i,, x_s, x_f\,, l; Z_q, CA\right) = 0 \qquad \text{(Production constraint)}$$

where *c* is a consumption vector, *q* is a production vector of farm output, x_s is the quantity of seed planted, x_f is the quantity of fertilizer applied on the farm, l is the labor wage, z_u are observable characteristics of the household, z_q are exogenous shifters of the farm's production function including the household's labor endowments and productive assets. The adoption of conservation agriculture is $CA = 1$ for adopters and 0 otherwise.

The hypothesis for this research is that household wellbeing across CA adopters is significantly different from non-CA adopters. A one-tailed power test to check if there is a difference between the means of households that adopted CA and CA non-adopters. These hypotheses are:

$$H_0: Y_{CA} - Y_{non-CA} = 0, \qquad H_1: Y_{CA} - Y_{non-CA} > 0$$

Rejecting the null hypothesis when is there no difference between the potential outcome of CA adopters and non-adopters will lead to a type I error, thus providing enough evidence to determine the power.

Power is calculated as;

$$Power = 1 - \Pr(type\ II\ error)$$

CHAPTER II

LITERATURE REVIEW

2.1 Smallholder Household Wellbeing

Smallholder farmers are defined as households that own and/or cultivate less than 2.0 ha of land (Singh et al., 2002). Smallholder farmers depend on the crops or animals produced on their holdings for subsistence and access to markets. Wellbeing indicators are difficult to establish. In the absence of consumption expenditures or direct measures of income, household wellbeing can be measured using indices that capture wealth related to the durable and non-durable property (Filmer and Pritchett, 2001; Sahn and Stifel, 2003)[1].

Some studies have used animal ownership and household construction materials to proxy wellbeing (Silici, 2010). In Mozambique, small animal ownership is omnipresent in almost every rural household providing another source of income for farmers (Njuki and Sanginga, 2013). Animals typically owned include cattle, pig, chicken, and goat.

2.2 Previous Research on CA

In terms of the overall impacts of CA practices, little on farm productivity and livelihood, research has been done on the relationship between CA and smallholder farmer household wellbeing. Most previous work has concentrated on clarifying the relationship between CA practices and crop productivity. Despite this, there is no firm consensus among researchers

[1] See McNair et al., 2015 for indices calculation

concerning CA impacts in different countries. For example, Place and Hazell (1993) find that land-improving investments in CA practices are not significant determinants of crop yield in Ghana, Kenya, and Rwanda. Hayes et al. (1997) and Nyangena and Kohlin (2008) also found similar results in Gambia and Kenya, respectively.

In Rwanda, Byiringiro and Reardon (1996) found that CA adopters reported higher crop productivity than CA non-adopters. This result is similar to the findings of other studies (for example, Keyser and Mwanza, 1997; Haggblade and Tembo, 2003; Adgebidi et al., 2004; Kaliba and Rabele, 2004; Menale et al., 2007; Kabamba and Kankolongo, 2009; Nyanga et al., 2011).

In Zambia, Haggblade and Tembo (2003) reported that CA adopters produced more maize output than their counterparts who practiced conventional farming. Kaliba and Rabele (2004) found a positive and statistically significant relationship between wheat yield and CA practices for Lesotho. Ng'ombe et al. (2017), found that households practicing CA realized more household income than households not practicing, in Zambia.

Simone et al. (2017) suggested that the adoption of CA may increase farmers' income if soil carbon sequestration saved through CA practices is linked to a payment of environmental service mechanism. McNair et al. (2015) found that CA adopters are more likely to participate in markets as net sellers compared to conventional farmers in Mozambique. However, their research did not identify any significant differences in the amount of maize produced by CA farmers and non-adopters. Kidane et al. (2019) reported a high increase in maize production on low and level farms treated with CA practices while conventional tillage practices applied on other farms yield lower maize production in Mozambique.

Mango et al (2017) analyzed the impact of CA adoption on of a food security indicator in Malawi, Zimbabwe and Mozambique. Their study reported that CA adopters in Malawi and Zimbabwe did not have significant differences in terms of food security compared to non-adopters. However, their research found a significance difference between CA adopters and non-adopters in terms of food security in Mozambique.

CHAPTER III

METHODOLOGY

3.1 Data and Data Source

The data for this study was a household survey conducted in March 2012 in the Manica and Tete provinces, Mozambique (McNair et al., 2015). In Tete, the survey was conducted in the Angonia and Ulongue districts. In Manica, the survey was conducted in the Barue district. Extension agents provided a list of communities as to where conservation agriculture had been introduced, well as a list of communities that had not been introduced to CA. From each separate list, villages were randomly selected for the survey. The surveyed regions have had many previous extensions efforts on CA practices (Grabowski and Mouzinho, 2013).

In total, twenty-two communities were surveyed. Twelve of these communities had been exposed to CA. Communities were designated as “exposed community” if there were current or previous extension efforts in the community training farmers on how to implement conservation agriculture practices on their farms. If there were no extension efforts in the community, the community was designated as an “unexposed community”.

The listed frame of villages included 5,256 smallholder households, of which 57 % lived in exposed communities. After villages were randomly selected, there were n =194 households in Barue district and n =365 households in Angonia and Ulongue districts. The response rate was

92% (n =514), of which 30% (n = 153) of the households practiced CA, 41% (214) lived in exposed villages but did not practice CA, and 29% (148) lived in unexposed villages. Systematic random sampling was used to select respondents that had not adopted CA in exposed and unexposed communities (Lohr, 1999).

Table 1: Village population and survey sample

	Angonia and Ulongue	Barue	N
Total number of farm households	3125 (60%)	2041 (40%)	5256
Exposed communities	2244 (81%)	757 (19%)	3001
Unexposed communities	1068 (45%)	1284 (55%)	2352
Survey Sample	365 (65%)	194 (35%)	559
Farm household surveyed			
Households practicing CA	97 (48%)	107 (52%)	204
Households not adopting CA	141 (66%)	73 (34%)	214
Non-adopters in unexposed communities	134 (91%)	14 (9%)	148

Source: McNair et al. (2014)

3.2 Household wellbeing indices

Household wellbeing in this study is measured using three indices that proxy household wealth. These indices were used in McNair et al. (2015) to measure household wellbeing in terms of farm tools and equipment owned, animal ownership, and house construction materials. The indices were constructed using Silici (2010) and Arian and Vos's (1996) methods.

The *asset index* measures wealth endowments related to productive assets. These items include; farm tools and transportation modes such as shovels, hoes, pumps, plows, wheelbarrows, and bicycles. The *animal index* measures wealth in terms of livestock ownership including, goats, chicken, cattle, and rabbits. The *house construction index* measures the quality of the construction materials of a house, the physical size of the house, access to electricity, and water (Zeller et al., 2006, McNair et al., 2015). The asset and animal indices are measured using the same method. Each index is measured by adding up the weight of the number of variables in an index (Silici, 2010).

The asset and animal indices are calculated as:

$$I = \frac{I}{N}\sum_{n=1}^{N} \sqrt[2]{x_n{}^2} \quad (1)$$

where *N* is the number of each variable in an index, and x_n is the score that corresponds to each variable in an index. Each index is normalized to facilitate comparisons across households (Böhringer and Jochem, 2007). Normalization consists of assigning a score to each variable in the index, depending on the quartile to which a household belongs. Scores are distributed into first, second, third, and fourth quartiles. For example, a score of 2 yields normalized score of 50. The normalization of scores ranges from 0 to 100.

Table 2: Calculation of the asset and animal indices: example

Indices/ Units owned	N	Quartile/Score	Normalized score
Asset index:			
Shovel	1	1	25
Axe	8	4	100
Plow	0	0	0
Hoe	3	3	75
Wheelbarrow	3	2	50
Bicycle	0	0	0
Animal Index:			
Goat	1	1	25
Cattle	15	4	100
Pig	2	2	50

For example, a smallholder farmer owning 1 shovel, 3 hoes, 8 axe, 3 wheelbarrows, 2 pigs, 1 goat and 15 cattle will have an asset and animal indices of (Table 2);

$$asset\ index = \frac{1}{6}\left(\sqrt[2]{25^2 + 75^2 + 100^2 + 50^2}\right) = 22.82$$

$$animal\ index = \frac{1}{3}(\sqrt[2]{50^2 + 25^2 + 100^2}) = 38.19$$

where the 25, 50, 75 and 100 correspond with quartiles 1, 2, 3, and 4, respectively.

The construction of the *house construction index* follows Arian and Vos's method (1996). The *house quality index* is also calculated using the same formula for asset and animal indices (equation 1).

Qualitative and binary variables included in the *house construction index* makes it difficult to normalized scores as in *asset index*. Categorical variables received a score of 0 or 100 using Arian and Vos's method (1996). For example, if a respondent reported "yes" (1) with respect to electricity, the variable receives a score of 100 (yes) and 0 (No). Scores were normalized by dividing the score level of a variable with the maximum score attainable.

Table 3: Calculations of the house construction index

Variables	Quality of materials	Quartile/Score	Normalized score
Wall	Mud brick	2	50
Floor	Dirt	1	25
Roof	Zinc	4	100
Bathroom	Outside	1	25
Electricity	No	0	0
Water source	Stream	3	75
Rooms	1	1	25

For example, a household having a house with the qualities above will have a *house construction index* of;

$$house\ quality\ index = \frac{1}{7}(\sqrt[2]{50^2 + 25^2 + 100^2 + 25^2 + 0^2 + 75^2 + 25^2}) = 14.29$$

where the normalized score for a water source is calculated as $\frac{3}{4} * 100 = 75$

3.3 Empirical Model and Specification

Matching estimation is used in this study to evaluate the effect of CA on household wellbeing. This method is useful in policy evaluation to determine the effect of a treatment on participants (Duflo et al., 2007). Matching estimation was used in this study to compare households which adopted CA (treatment group) to non-adopter households (control group) based on similar household characteristics. The main advantage of using matching estimators is that it does not require specifying a functional form of the outcome equation.

The effects of CA on household wellbeing is measured by the average treatment effect on the treated (ATT). The ATT is defined as the mean difference in the potential outcome variable between CA adopters after receiving the treatment with the counterfactual if CA adopters did not receive the treatment. The ATT is defined as (Wooldridge, 2001):

$$ATT = E(Y(1)|D = 1, X_i) - E(Y(0)|D = 1, X_i) \qquad (2)$$

where $Y(1)|D = 1$ is the potential average outcome of households which adopted CA,

$Y(0)|D = 1$ is the potential average outcome of CA adopters if they had not adopted CA, and X_i is a vector of household, farm production, market, and community characteristics.

3.4 Variables Selection for the Matching Algorithm

Covariates selection is very important to matching estimation. The inclusion of variables in the model was based on Pearson's correlation test (Appendix 2). The null hypothesis for this test is; $H_0: \rho = 0$ where ρ is the correlation coefficient between variables and wellbeing indicators used in the model. Only variables correlated to the wellbeing indices and weakly or not correlated to the treatment variable were included for the matching estimations. This is because variables that are strongly correlated to the treatment but not with the outcome can decrease precision and increase bias of matching estimates (Brookhart et al., 2006; Ng'ombe et al., 2017). The definitions and descriptions of the variables used in the model are in Appendix 1.

3.5 Propensity Score

The propensity score is the conditional probability of adopting CA given smallholder household attributes (Rosebaum and Rubin 1983; Heckman et al., 1998; Smith and Todd, 2005; Wooldridge, 2005). Propensity scores are used to minimize bias in observational studies. The propensity score is;

$$P(X) = \Pr(D = 1|X) \tag{3a}$$

where D is a dummy variable that equals 1 for CA adopters and 0 otherwise, and X is a vector of the covariates that affect the adoption of CA. The propensity scores were estimated using logistic regression.[2] The odds ratio of the logit model is;

$$Prob(Y_i = 1) = \ln\left(\frac{\pi}{1-\pi}\right) = b_0 + b_1x_1 + b_2x_2 + \cdots + b_kx_k \tag{3b}$$

where π is the expected proportional response for the logistic model, b_1 to k are parameters of interest and, x_1 to k are covariates hypothesized to determine CA adoption. There are two key assumptions underlying matching procedure; an overlap condition (common support) and conditional independence[3]. The conditional independence assumption restricts the dependence between the adoption of CA and the potential household wellbeing outcomes.

Adoption of CA is independent given household covariates X is defined as,

$$(Y_1, Y_0) \perp D|X \tag{3c}$$

---

[2] See Hosmer and Lemeshow, 1989; Armitage and Berry, 1994; Altman 1991; McCullagh and Nelder, 1989; Cox and Snell, 1989; Pregibon, 1981 for the derivation of the logit model.
[3]. Also called Stable-Unit Treatment Value Assumption (SUTVA) or Unconfounded assumption.

where $\perp$ indicates conditional independence, X is a vector of the household covariates that affect the adoption of CA. The conditional independence assumption requires that all household covariates relevant to the adoption of CA should be included in X.

The overlap condition assumes that the probability assigned to both CA adopters and non-adopters for each covariate is positive. The overlap condition is stated as follows;

$$0 < \Pr(D = 1|X) < 1 \tag{3d}$$

Firstly, this assumption implies that the proportion of CA adopters and non-adopters must be greater than 0 and less than 1 for each variable of X. Secondly, the overlap condition assumes that there is sufficient overlap in the characteristics of CA adopters and non-adopters to find adequate matches.

Balancing tests were carried out to ensure the validity of the overlapping condition. The balancing tests verify whether the average propensity score is the same for both the CA adopters and the CA non-adopters after matching. After matching, there should be no differences in the distribution of the covariates between CA adopter and CA non-adopter households (Sianesi, 2004). This condition implies that;

$$\Pr(D_i = 1|X) = \Pr(D_i = 0|X) \tag{3e}$$

Estimation of the propensity scores is an important step in the evaluation of the impacts. Ideally, it is possible to obtain the same propensity score for CA adopters and non-adopters. However, the propensity scores are continuous variables, thus making it impossible to get a CA adopter with the same propensity score as its counterfactual. It is, therefore, important to look for the non-adopter that matches CA adopters with the same propensity scores.

3.5.1 Matching Methods

Several methods proposed by Rosebaum and Rubin (1985) were used in this study to perform the matching estimation. The methods match CA adopters with non-adopters by their propensity scores. I also performed a coarsened exact match that does not use propensity scores to match treated and control groups. Performances of each matching estimator is determined through the trade-off between bias among covariates and variances of the ATT. The percentage reduction of bias by each matching estimator is presented in Appendix 3. Bias reduction using the coarsened exact matching was 70 %.

3.5.1.1 Nearest Neighbor matching (NNM)

Nearest neighbor matching generally selects *k* matched controls for each treated unit. The simplest NNM uses a "greedy" algorithm, which considers each treated unit one at a time, selecting the closet unmatched control unit. This estimator was derived by Abadie and Imbens (2006, 2011) and was previously implemented in Stata (Abadie et al., 2004). Five variants of the NNM was used for the matching estimation; 1-to-1 neighbor, 1-to-5 neighbor, with replacement or without replacement, and with caliper size. Rosebaum and Rubin (1985) proposed to use a caliper size of a quarter of the standard deviation of the propensity scores.

3.5.1.2 Kernel matching

This method uses a weighted average of all individuals in the non-adopter group to construct a counterfactual outcome (Ichimura et al., 1998). For example, the ATT for this method is calculated as (Ichimura et al., 1998):

$$ATT = \frac{1}{N}[E(Y(1)|D = 1, X) - E(Y(0)|D = 1, X)]$$

where N is the number of non-adopters retained for the estimation. The gaussian (normal) and epanechnikov kernels were used in this analysis.

3.5.1.3 Manahalobis matching

This matching method uses randomly ordered individuals and then calculates a distance between the first treated individual (CA adopter) and all the controls (non-adopters). The process is repeated until matches are found for CA adopter households. The one-to-one with replacement option and 1-to-5 with replacement options were used for this matching algorithm.

3.5.1.4 Coarsened exact matching (CEM)

Coarsened exact matching is a monotonic imbalance-reducing matching method, which means that the balance between the treated and the control groups is chosen by ex-ante user choice based on the empirical distributions of variables (Iacus et al., 2009). Observations are stratified into groups to eliminate observations not needed in the matching estimation. This process is called coarsening, where only the required number of matches (uncoarsened data) are retained for estimation. The CEM algorithm performs exact matching on coarsened data to determine matches and then passes on the uncoarsened data from observations that were matched to estimate the sample average treatment effect on the CA adopters.

3.6 Standard Errors of ATT

Standard errors obtained after matching are inappropriate for inference pertaining to ATT differences because the standard errors are not accounted for in the estimation of the propensity scores. Lechner (2002) proposed bootstrapping as a solution to reduce standard errors bias. Standard errors were calculated using a bootstrapping method with *n* number of replications following Andrews and Buchinsky's method (2000). This a three-step procedure to determine the optimal number bootstrapped replications. The first step was to determine an initial replication size (n1) from the sample. In step two and three, the variables used in the model are bootstrapped in n1 replications and refined to obtain a final estimate of the final number of replications.

3.7 Descriptive Statistics

The descriptive statistics for this study are similar to the results of McNair et al. (2015). Turkey's multiple comparison test was conducted to test for differences between the means variables across each group at a 5% significance level.

3.7.1 Household wellbeing indicators

The difference in means for asset index between CA farmers and conventional farmers in exposed villages is significantly different at 5% level (Table 4). Farmers practicing CA reported higher wellbeing related to farm tools endowments compared to non-adopters in exposed and unexposed communities. This is because early CA adopters have more resources. They tend to be good farmers, and less risk-averse than later CA adopters.

Households practicing CA reported an average of 33.72 points compared to an average of 26.66 points and 25.33 points for non-adopters in exposed and unexposed villages (Table 4). The means difference between CA adopters and non-adopters in exposed villages was significantly different at the 5% level and not significantly different for non-adopters in both exposed and unexposed villages.

The house construction index was significantly different at 5% level among CA adopters and for non-adopters in both exposed and unexposed villages. Households practicing CA reported a higher wellbeing average of 48.38 points for house quality index compared to non-adopters (43.38 points and 39.85 points) in exposed and unexposed respectively. This means that CA adopters use more durable materials in the construction of their houses.

3.7.2 Household and Farm Characteristics

Education was not significantly different across CA adopters and non-adopters in both exposed and unexposed communities (Table 4). The average response for primary school attendance for

CA farmers and conventional farmers in exposed communities was 4.14% and 3.83%, respectively. Non-adopters in unexposed villages reported a response rate of 3.69%. Household size was not significantly different across CA households and non-adopter households. The average for CA households was approximately seven persons per household and a mean of six persons for non-adopters in exposed communities. The means comparisons for the age of the head of the household was significantly different among the three groups. Households practicing CA and non-adopters in exposed villages reported an average of 44.66 years and 42.78 years, respectively. The average age of the head of the household for non-adopters in unexposed villages was 40.97 years.

The means differences for female headed household was significantly different among CA households and non-adopters in exposed and unexposed villages. Households practicing CA reported an average of 0.14%, and non-adopters in exposed and unexposed villages reported an average of 0.19 % and 0.26 %. This means that headed male households are more engaged in CA practices.

Income generated from farm activities is significantly different among CA adopters and non-adopters in exposed villages. CA farmers reported an average increase of 83.7 % income from farm, while non-adopters in exposed villages reported an average increase of 71.2% income from farm. The differences in income from the farm were not significantly different among different between CA farmers and non-adopters in unexposed communities. Income for labor wages was not different among groups (Table 4).

The number of persons in a household having employment was not significantly different among CA households and non-adopters in exposed and unexposed communities. The total land holdings were not significantly different for households in exposed villages. CA farmers owns more significantly different land compared to conventional farmers in unexposed communities having (average of 5.00 hectares). The total landholdings were also different between conventional farmers in exposed and unexposed villages at the 5% significance level. Non-adopters in exposed communities had an average of 4.37 hectares compared non-adopted in unexposed communities holding an average of 3.31 hectares.

Households practicing CA were significantly different from non-adopters in unexposed communities related to market transactions with large vendors. The response rate for transactions with large vendors was higher by18% for CA households, and higher by 17% and 10% for non-adopters in exposed an exposed community, respectively. Households practicing CA may have an increase in maize production given adoption of CA, thus may sell surpluses in the market. CA farmers are more present in market transactions as net sellers (McNair et al., 2015).

Females in engaging in agricultural markets were 40% for CA households, 46 % for non-adopters in exposed villages; and 42% in unexposed villages. The means difference for female net sellers were significantly different between households in exposed villages and households in unexposed villages. An increase in quantity of maize produced and quantity of maize purchased was not significantly different across groups in both exposed and unexposed villages.

Table 4: Means comparisons of smallholder household characteristics

	Exposed Communities								Unexposed Communities			
	CA adopters				Non-adopters				Non-adopters			
	Mean	Std.dev	Min	Max	Mean	Std.dev	Min	Max	Mean	Std.dev	Min	Max
Dependent Variables												
Asset index	42.22*	13.77	0	77.73	34.78**	13.85	0	70.71	32.86**	13.23	0	64.95
Animal index	33.72*	20.78	0	76.38	26.66**	21.08	0	89.56	25.33**	19.60	0	70.71
House quality index	48.38*	14.23	20	84.37	43.41**	15.60	0	79.93	39.85***	15.63	0	84.37
Independent Variables												
education (dummy)	4.14*	3.10	0	16	3.83*	3.02	0	12	3.69*	3.01	0	8
household size(count)	6.51*	2.93	2	18	6.00 *	2.76	1	25	5.87*	2.66	1	16
age head household (years)	44.66*	12.70	24	91	42.78**	14.09	19	85	40.97***	13.19	16	67
female head of household (dummy)	0.14*	0.35	0	1	0.19**	0.40	0	1	0.26***	0.44	0	1
income farm (%)	8.37*	2.84	0	10	7.12**	3.59	0	10	7.09**	3.63	0	10
income labor (%)	1.22*	2.64	0	10	2.20*	3.43	0	10	2.03*	3.34	0	10
number of employed (count)	3.95*	2.11	1	13	3.47*	2.00	1	19	3.36*	1.79	0	9
total field size (ha)	5.00*	5.78	0.3	50	4.37*	5.50	0.1	68	3.31**	2.93	0.2	20
large vendor (dummy)	0.18*	0.38	0.00	1.00	0.17*	0.37	0	1	0.10**	0.31	0	1
female decision (dummy)	0.40*	0.49	0	1	0.46*	0.50	0	1	0.42**	0.50	0	1
maize produced (%)	0.92*	0.18	0	1	0.88*	0.22	0	1	0.86*	0.20	0	1
maize bought (%)	0.18*	0.17	0	1	0.12*	0.22	0	1	0.14*	0.20	0	1

Sources: Values calculated by the author. Note: Means followed by the same number of asterisks are not significantly different at 5% (Turkey's multiple comparison test).

CHAPTER IV

FINDINGS

4.1 Model Diagnostics

The kernel density plots indicate the probabilities of individual smallholder households who adopted CA and households which did not adopt CA are within 0 and 1 (Equation 3d). The overlap condition (common support) was satisfied, as seen by the two kernel distributions (Figure 1), where the x and y axes are the propensity scores and the densities of the propensity scores, respectively. The shape of the both groups describes the disparities of household characteristics among smallholder households.

The matching of households with similar characteristics was satisfied after matching (Equation 3e and Figure 2). The graph on the left (Figure 2) shows matched CA households and non-adopters in exposed communities. I can infer from that graph that CA adopters and non-adopters in exposed communities were similar in terms of household characteristics. This is because of the close proximity of households in exposed communities, thus sharing common characteristics. The graph on the right (Figure 2) shows matched CA adopters and non-adopters in exposed and unexposed communities, respectively.

Figure 1: Unmatched sample for exposed and unexposed communities

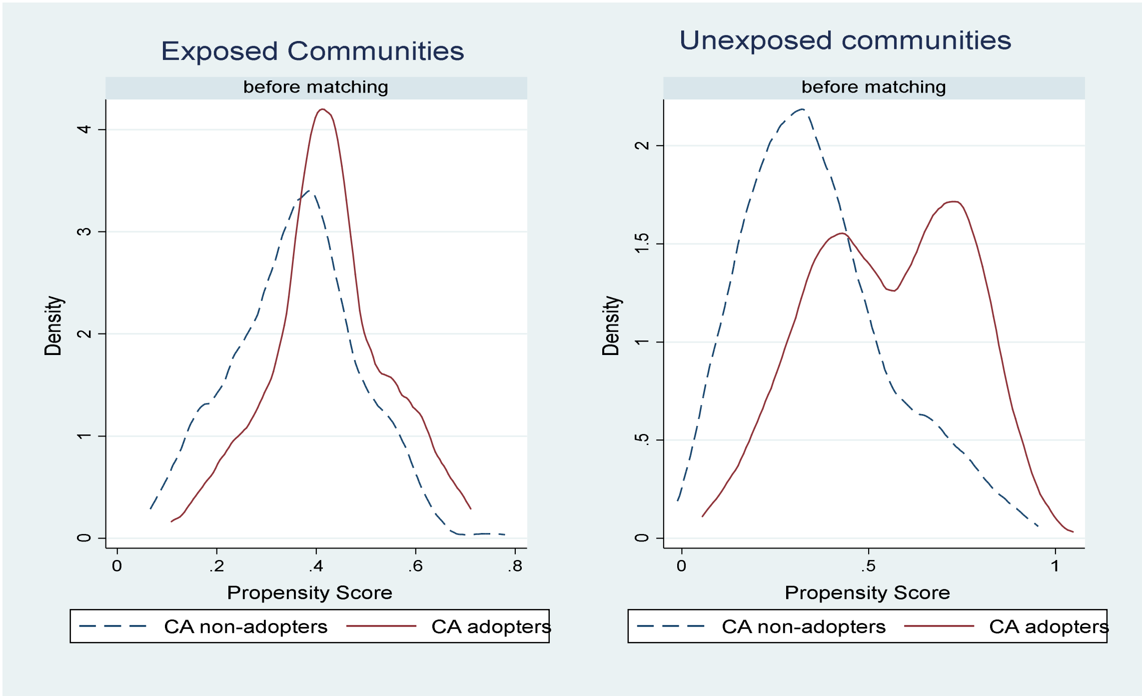
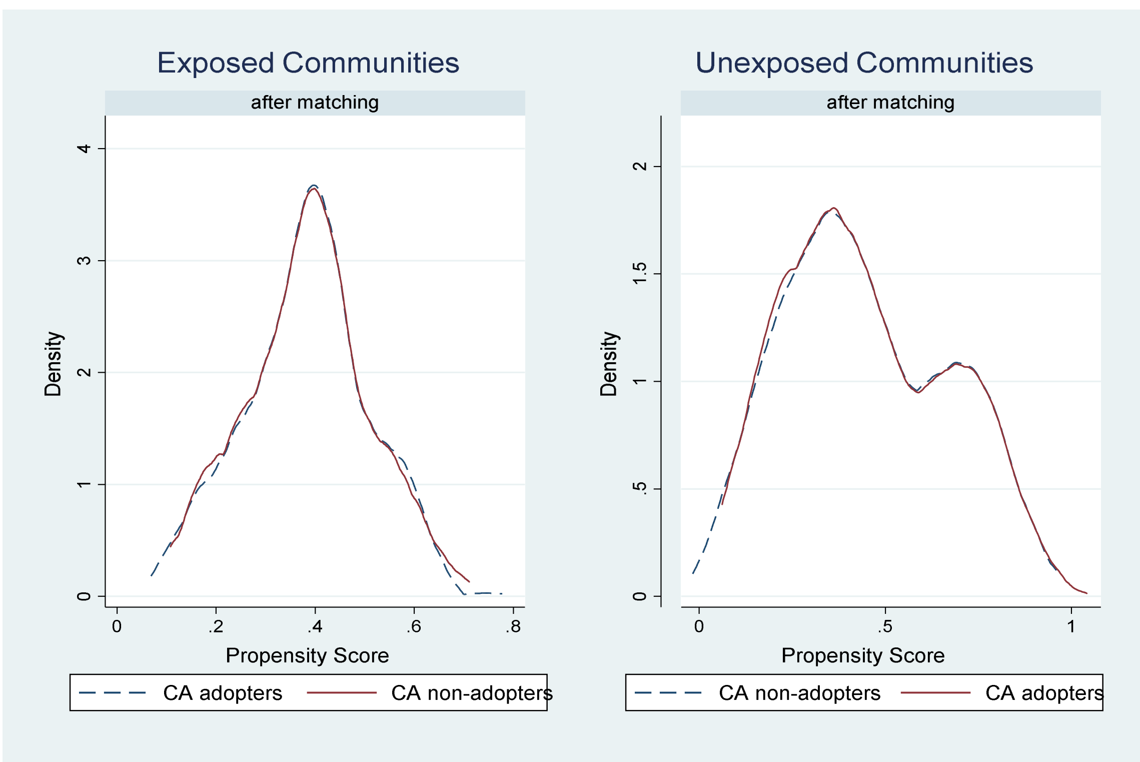


Figure 2: Matched sample for exposed and unexposed communities



4.2 Impact estimation of CA on smallholder wellbeing

Tables 6 and Table 7 highlight the ATT for CA adopters and the counterfactual group, and the number of observations retained for each matching estimator (equation 2). The ATT of the household wellbeing outcomes are reported under the actual condition and their counterfactual condition (equation 4a). The treated column for each wellbeing outcome is the actual wellbeing outcome households that practiced CA adopters realized after adopting CA. The control column for each outcome variable is the counterfactual outcome CA adopter households would have realized if they had not adopted CA. The difference (DID) column for each outcome variable is the difference between the actual outcome and its counterfactual.[4] The last columns (Tables 6 and 7) show the number of observations that were retained for each matching procedure. Households that violated the overlap condition in the matching analyses were dropped in order to reduce bias.

4.2.1 Estimates of CA on smallholder wellbeing indices in exposed communities

Table 4 highlights the results of the ATT of asset index, animal index, and house quality index in exposed communities. The results show that households that practiced CA realized positive higher wellbeing indices in terms of farm asset and house construction indices, with the adoption of CA compared to the counterfactual if they had not adopted CA. The wellbeing outcome related to livestock ownership (*animal index*) decreased low with the adoption of CA.

The ATT is significantly different for asset and house quality indices between CA adopters and CA non-adopters, thus rejecting the null hypothesis at 1%, 5%, and 10% significance level for most of the matching estimators. The asset and house quality indices were not significantly different using the coarsened exact match.

[4] Difference-in-difference (DID) is used simultaneously with the average treatment effect on the treated (ATT)

For the animal ownership index, the ATT of the kernel match (gaussian), mahanalobis match (1-to-1 with replacement), and coarsened exact match were significantly different at 5% and 10% level. Other matching methods fail to reject the null hypothesis that CA adopters are better-off in terms of animal ownership index compared to non-adopters. This was expected because CA practices are encouraged to retain require crop residues to increase soil moisture capacity making, thus making it difficult for CA adopters to feed livestock (FAO, 2011b). The number of observations retained for the ATT estimation varies from each matching estimator from 27 to 355. The coarsened exact matching had the lowest number of observations for ATT estimation.

Table 5: Matching estimates of the ATT in exposed communities

Method	Asset index			Animal index			House quality index			Number of observations retained for the estimate of the ATT
	Treated	Control	Difference	Treated	Control	Difference	Treated	Control	Difference	
Nearest-neighbor match:										
1 without replacement	43.50	38.54	4.96** (2.03)	35.53	32.50	3.03 (3.28)	49.31	45.15	4.16** (1.78)	355
1 without replacement and caliper =0.25 SD	41.79	38.35	3.44** (1.49)	33.62	32.29	1.33 (2.36)	48.62	45.34	3.28* (1.87)	342
1 with replacement	43.50	39.71	3.79* (2.05)	35.53	33.14	2.39 (3.44)	49.31	45.84	3.47 (2.47)	355
1 with replacement and caliper = 0.25 SD	42.93	38.77	4.16** (2.09)	35.07	31.77	3.30 (3.60)	49.10	45.56	3.54 (2.70)	351
5 with replacement	43.50	38.42	5.08*** (1.56)	35.53	31.92	3.61 (2.74)	49.31	45.89	3.42* (2.20)	355
5 with replacement and caliper = 0.25 SD	42.93	38.33	4.60** (1.61)	35.07	31.90	3.17 (2.74)	49.10	45.63	3.47* (2.15)	351
Kernel match:										
Gaussian	43.50	37.98	5.52*** (1.21)	35.53	31.17	4.36** (2.16)	49.31	45.13	4.18** (1.77)	355
Epanechnikov	43.50	38.82	4.68*** (1.25)	35.53	32.34	3.19 (2.30)	49.31	45.28	4.03** (1.78)	355
Mahalanobis match:										
1 with replacement	43.50	38.72	4.78*** (1.46)	35.53	31.38	4.15* (2.77)	49.31	41.78	7.53*** (2.31)	355
5 with replacement	43.50	38.20	5.30*** (1.31)	35.53	31.11	4.42* (2.45)	49.31	44.11	5.20** (2.06)	355
Coarsened exact match	n/a	n/a	2.31 3.98	n/a	n/a	18.98** 6.60	n/a	n/a	4.75 5.82	26

Sources: Values calculated by the author. Notes: ***, **, * denote 1%, 5% and 10% respectively. Bootstrapped standard errors are in parentheses. Number of bootstrapped of replications (N) is 2538 (Andrews and Buchinsky, 2000).

4.2.2 Estimates of CA on smallholder wellbeing indices in unexposed communities

Table 7 presents the results of the matching analysis between CA adopters in exposed villages and non-adopters unexposed villages. The results show that CA households realized positive higher wellbeing outcomes in terms of *asset index* and *house construction index,* and a lower wellbeing in livestock ownership (*animal index*) compared to CA non-adopters in unexposed communities.

The Households practicing CA realized higher wellbeing outcomes in terms of asset accumulation (*asset index*) and *house construction index* given the adoption of CA, compared to its counterfactual if they had not been adopted CA. The ATT for *asset index* and *house construction index* was statistically significant at 1%, 5% and 10% p-values for most of the matching methods.

The coarsened exact match reported a negative ATT and a positive ATT for asset and house construction indices respectively. For *animal index*, the ATT was significantly different at $p < 0.10$ for NNM (1-to-1 with replacement) estimator, while the other matching estimators fail to reject the null hypothesis. The explanation for the non-significant difference in livestock ownership (*animal index*) among smallholder households in exposed and unexposed communities is similar to the reason given in section (4.2.1). The number of observations retained for the ATT estimation varies from each matching estimator from 17 to 304.

Table 6: Matching estimates of the ATT in unexposed communities

Method	Asset index			Animal index			House construction index			Number of observations retained for the estimate of the ATT
	Treated	Control	Difference	Treated	Control	Difference	Treated	Control	Difference	
Nearest-neighbor match:										
1without replacement	43.10	35.68	7.42** (2.87)	35.07	28.86	6.21* (4.23)	49.09	41.59	7.50*** (1.87)	302
1without replacement and caliper =0.25 SD	40.41	36.95	3.46** (1.73)	30.33	31.94	-1.61 (2.81)	48.14	42.20	5.94** (5.94)	258
1 with replacement	43.10	38.64	4.46** (2.25)	35.07	32.15	2.92 (3.97)	49.09	41.63	7.46 ** (2.97)	302
1 with replacement and caliper = 0.25 SD	43.11	38.64	4.47** (2.16)	35.07	32.15	2.92 (3.99)	49.09	41.63	7.46** (2.94)	302
5 with replacement	43.10	39.04	4.06** (1.72)	35.07	34.60	0.47 (3.35)	49.09	41.60	7.49** (2.46)	302
5 with replacement and caliper = 0.25 SD	43.10	39.04	4.06** (1.39)	35.07	34.53	0.54 (3.28)	49.10	41.65	7.45** (2.40)	302
Kernel match:										
Gaussian	43.10	39.05	4.05** (1.39)	35.07	33.46	1.61 (2.83)	49.09	40.80	8.29*** (2.02)	302
Epanechnikov	43.10	39.25	3.85** (1.54)	35.07	33.98	1.09 (3.02)	49.09	40.70	8.39*** (2.14)	302
Mahalanobis match:										
1 with replacement	43.50	40.02	3.48** (1.73)	35.53	34.96	0.57 (2.88)	49.31	38.30	11.01*** (2.22)	304
5 with replacement	43.50	38.72	4.78*** (1.48)	35.53	32.21	3.32 (2.69)	49.31	40.06	9.25*** (2.02)	304
Coarsened exact match	n/a	n/a	-8.91 5.98	n/a	n/a	-4.04 11.13	n/a	n/a	5.99 7.03	17

Sources: Values calculated by the author. Notes: ***, **, * denote 1%, 5% and 10% respectively. Bootstrapped standard errors are in parentheses. Number of bootstrapped replications (N) is 1766 (Andrews and Buchinsky, 2000).

CHAPTER V

CONCLUSIONS

5.1 Conclusions

The objective of this study was to determine the impact of CA on smallholder household wellbeing in Mozambique. The study was achieved using survey data collected in areas of ongoing extension efforts to promote CA (McNair et al., 2015). Furthermore, the study employed three matching methods that use propensity scores and the coarsened exact match method to help match smallholder households practicing CA with a household that did not adopt CA.

The following conclusions could be drawn from the results. Firstly, households that adopted CA are better off in terms of farm-related tools (*asset index*) and quality of house constructed (*house construction index*) compared to households that did not adopt CA. Also, households adopting CA and CA non-adopters are not much different in terms of animal ownership (*animal index*).

Secondly, smallholder households in exposed communities realized higher wellbeing indices after adopting CA than if they had not adopted CA. Finally, a one-tailed test was conducted to determine if wellbeing indicators were different between CA adopters and CA non-adopters in exposed communities. The test rejected the null hypothesis at 5% significance level revealing that *asset index* is significantly different (effect size is 0.26) across CA adopters and non-adopters in exposed communities with a power of 99.95 percent; *animal index* is significantly different (effect size = 0.16) across CA adopters and non-adopters in exposed villages with a power of 90.92 %, and *house construction index* significantly (effect size = 0.16) across CA adopters and non-adopters in exposed villages with power of 89.58%. Therefore, I conclude that there exist differences in observable characteristics among CA adopters and non-adopters in exposed communities.

5.2 Recommendations

The results from this study are particularly important to design policies for continuous extension efforts in promoting CA practices to improve smallholder household wellbeing in Mozambique. This is motivated by the positive results that household which adopted CA realized higher wellbeing indicators of 49.6 percent and 41.6 percent in *asset index* and *house construction index* respectively than if they had not adopted CA. However, these returns call for extensive work on CA practices. Lastly, this study recommends that CA should continue to be promoted through government agencies (Ministry of Agriculture in Mozambique) and non-governmental organizations to increase returns in the long-term and not just in short periods. This will reduce the magnitude of the gap between CA adopters and non-adopters.

5.3 Further research

Regarding the decline in agricultural productivity in most SSA countries, there is motivation to continue promoting and monitoring the impacts of agricultural technology on smallholder farmers. This is because smallholder contributes to more than 70 percent of agricultural productivity in most developed countries, and even in Mozambique. Furthermore, incoming research should rather be a panel to help control for time-invariant characteristics that might have clouded cross-sectional studies and thereby report less robust results. Also, interest in research should be directed to the impact of multiple agricultural technologies to increase agricultural productivity.

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APPENDICES

Appendix 1

Hypothesized effect of household characteristics on smallholder household wellbeing

Variable name	Description	Expected effect on household wellbeing
Dependent Variables		
Asset index	Indicator capturing farm asset ownership	+
Animal index	Indicator capturing animal ownership	+/-
House quality index	Indicator capturing house quality and material	+
CA adopt	CA adoption (1=yes, 0 otherwise)	+
Independent Variables		
Household characteristics		
education	Head of household has attended primary school (1=yes, 0 otherwise)	+
household size	All members of household in primary residence (count)	-
age head household	Age of head of household (years)	+/-
female head of household	Female headed household (1=yes, 0 otherwise)	-
income farm	Income generated from farm (percent)	+
income labor	Income generated from employment (percent)	+
number of employed	Number of employed in the household (count)	+/-
Production characteristics		
total field size	Total land holding per household (ha)	+
Market characteristics		
large vendor	Transactions with a large vendor (=1 if yes, 0 otherwise)	+
female decision	Female decision to participate in market as net seller (=1 if yes, 0 otherwise)	+/-
maize produced	Quantity of maize produced (percent)	+
maize bought	Quantity of maize bought (percent)	-
Community characteristics		
barue (dummy)	Barue community (=1 if yes, 0 otherwise)	+

Appendix 2

Pearson's correlation test between dependent and independent variables

	Asset index	Animal index	House construction index
education (dummy)	0.325	0.141	0.115
household size (count)	0.452	0.348	0.199
age head household (years)	0.198	0.194	0.194
female head household (dummy)	-0.367	-0.223	-0.157
income farm (%)	0.136	0.192	0.054
income labor (%)	-0.190	-0.232	-0.112
total field size (ha)	0.361	0.324	0.256
number of employed	0.444	0.283	0.201
maize produced (%)	0.225	0.234	0.901
maize bought (%)	-0.252	-0.245	-0.088
large vendor (dummy	0.278	0.210	0.076
female decision (dummy)	-0.174	-0.151	-0.107
Barue (dummy)	0.523	0.451	0.146

Source: Author's calculation

Appendix 3

Bias Matching Estimates of the ATT in Exposed Communities

Method	%Bias Reduced		
	Min	Max	Average
Nearest-neighbor match:			
1 without replacement	0	9.51	4.17
1 without replacement and caliper = 0.25 SD	0	14.72	6.59
1 with replacement	0.40	22.53	7.46
1 with replacement and caliper = 0.25 SD	0.41	18.23	3.18
5 with replacement	0	10.51	3.02
5 with replacement and caliper = 0.25 SD	0.08	11.93	3.72
Kernel match:			
Gaussian	1.79	12.56	2.66
Epanechnikov	0.41	11.06	3.62
Mahalanobis match:			
kernel -gaussian	0	14.49	2.42
1-to-1 with replacement	0	31.68	6.73
5-to-5 with replacement	1.14	32.27	5.85

Source: Author calculations

Bias Matching Estimates of the ATT in Unexposed Communities

Method	%Bias Reduced		
	Min	Max	Average
Nearest-neighbor match:			
1 without replacement	6.09	55.12	20.66
1 without replacement and caliper = 0.25 SD	0	18.96	2.80
1 with replacement	0	29.80	3.23
1 with replacement and caliper = 0.25 SD	0	29.80	3.23
5 with replacement	0.32	13.31	4.20
5 with replacement and caliper = 0.25 SD	0.32	13.09	4.58
Kernel match:			
Gaussian	0.54	9.16	3.52
Epanechnikov	0.22	9.41	1.83
Mahalanobis match:			
kernel -gaussian	0	6.85	1.44
1-to-1 with replacement	0.75	18.98	7.01
5-to-5 with replacement	0	26.64	8.66

Source: Author calculations

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